Double-Shift High Schools and School Performance: Evidence from a Regression Discontinuity Design*

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Abstract

Policymakers in developing countries often resort to double-shift schooling systems in order to maximize schooling supply under tight budget constraints. There is however some concern that this strategy trades off equality in school quality for cost effectiveness. In this paper we investigate whether or not this is the case. In order to overcome the selection problems in the assignment to the different shifts, we exploit the discontinuity in the assignment of students to the afternoon shift given their middle school GPA. Using data from administrative records and a socioeconomic survey in a high school system in Mexico City, we find that being assigned to the afternoon shift leads to a 12 percentage points increase in the probability of dropping out for female students, and a 12.4 percentage points decrease in this probability for male students. We then explore on the mechanisms behind this asymmetric response, and conclude that women are more negatively affected by worse peers than men, men respond more positively to having more homogenous groups, and men respond more positively to their relative ranking in their class than women.

Keywords: School performance; high school; double-shift schools; RDD; peer effects; tracking; relative comparisons; Mexico.

JEL Codes: I20, I21, I24, I28, O54.

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* All errors and omissions are the sole responsibility of the authors.

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1. Introduction

Developing countries face serious budget constraints that hinder their ability to expand the education supply. As a result, policymakers have often resorted to double-shift schools (DSS) to increase the supply of school spaces: the school opens for a morning-shift and an afternoon-shift, effectively doubling the amount of spaces available in a school without the need to build additional infrastructure. There are, however, some drawbacks to double-shift schools. It is argued that the afternoon-shifts have lower quality professors and lower quality students due to negative self-selection. In consequence, students attending the afternoon shift may have lower school performance vis-à-vis the students in the morning shift. An analysis of the causal effect of the double-shifts on school performance is difficult precisely because of this selection. In this paper, we aim to overcome this estimation challenge by using the exogenous assignment rule (based on middle school grade point average) of students to the morning and afternoon shifts in Mexican high schools, which allows us to implement a regression discontinuity design.

The Mexican Ministry of Education began using multiple-shifts during the sixties as a way to expand schooling supply.[1] Currently, the double-shifts are a widespread practice in public schools at all schooling levels. At the high school level, Mexico has achieved 100% coverage of the students applying to high school. However, the dropout rates in high school are still very high: only 62 percent of the entering class finishes high school. In addition to this, if one looks at the dropout rates in the morning and afternoon shift, one finds a stark difference. In the morning shift 75 percent of students are able to complete high school, whereas in the afternoon shift only 36 percent manage to complete high school.[2] This difference in high school completion between shifts led us to ask ourselves if, despite its cost-effectiveness, the implementation of the multiple

[1] Even though we will be talking about double shifts (a morning and an afternoon shift), some public schools in Mexico offer three different shifts: morning, afternoon and night shifts. The night shifts are mostly used by adults.

[2] These figures come from administrative records from the School of Sciences and Humanities (CCH for its Spanish acronym) which are a high school system pertaining to the National Autonomous University of Mexico (UNAM for its Spanish acronym). The Ministry of Education does not have statistics disaggregated by shifts at the national level.

shifts is leading to inequality of opportunities between students. Specifically, is the afternoon shift hindering the opportunities of students to have access to schooling quality, or is this just the effect of negative selection in the distribution of students across shifts?

The possibility that the DSS prevent some students to finish high school could have major economic effects. Zimmerman (2014) uses a regression discontinuity design (RDD) to show that the gain in income associated with admission to university of a marginal student is high. Students just above the cutoff grade of high school earn an average of $1,593 per month more than those who are just below, this represents a considerable efficiency gain. These implications could be generalized to the case of high school students who could see their future truncated when they are assigned to the afternoon shift, and this loss could even exceed the savings generated by the use of DSS.

In his analysis, Bray (2000) highlights that the main benefit of adopting DSS is the reduction of the unitary education cost. This is mainly achieved because of three factors: a more efficient use of educational infrastructure, even if maintenance costs increase; a more efficient use of human capital because professors may be allowed to teach in both shifts; and a reduction in the effective education time for professors and students that can be invested in other activities, which is due to the reduction of available classroom time. In contrast, some potential costs arising from the adoption of DSS are: 1) the necessity to hire child care services for working parents, 2) the necessity of additional tutoring to compensate the reductions on classroom time, and 3) social problems arising from the bad use of students' leisure time.

The figures on school desertion support the common belief that the morning shift is "better" than the afternoon shift among parents and students. In fact, parents strive to get their children enrolled in morning shift instead of the afternoon one. However, there is no evidence to support these beliefs; that is, that the afternoon shift is inherently of lower quality (Linden, 2001). People justify this prior on the basis that the afternoon shift receives the worst students, but there is no consensus among researchers that this is actually true. In fact, there is very scant literature on the impact of this education policy, and most of the evidence does not have a causal interpretation.

The school principals tend to first allocate students to the morning shift, and once the spaces are exhausted in this shift they begin enrolling students in the afternoon shift. In general, principals do not follow a uniform criteria in the allocation of students to the different shifts. Notwithstanding, students' characteristics in each shift differ making it very difficult to estimate the causal effect of this policy. In his study, Linden (2001) compared one-shift schools vis-à-vis double-shift schools in OECD countries, and concludes that the latter schools offer an adequate education and could be used as a convenient educational policy.

Cardenas (2011) carried out an extensive review of the literature on DSS. He summarizes it in three general points: first, he finds little empirical evidence about the differences in performance between shifts; second, he concludes that principals, teachers and students face different challenges in every turn; and finally, he says that previous research has identified a segregation system that assigns students based on their socioeconomic profile (Saucedo-Ramos, 2005). He also shows that, when comparing both shifts, on average there are more poor students, lower performance on standardized tests, as well as higher dropout and failure rates in the afternoon shift. Neither author is capable to give a causal argument, since their identification strategy cannot control the selection problems in the allocation of shift.

Sagyndykova (2013) studies the effect of DSS in Mexican elementary schools and concludes that DSS is an appropriate solution for countries with limited budgets. She applies the Heckman selection model to measure the effects of observable characteristics on student performance, and finds a positive effect for being assigned to the morning shift. However, the "Oaxaca Decomposition" shows that this effect can be explained by observable characteristics of the student, school and teachers. Her results show that the self-selection of students explains the apparent achievement gap between students from different shifts.

In this paper, we aim to determine if DSS, which has helped to provide universal access to schooling in Mexico, leads to a reduction in school quality in the afternoon shift. In particular, we are interested on whether the observed differences in school performance between the morning and afternoon shifts are causal. To this effect, we will use several measures of performance, but our main focus will be on dropout rates. In order to identify the causal effect of the afternoon shift on school performance we will exploit the rules of assignment in a system of UNAM's high schools known for its acronym, CCH (School of Sciences and Humanities). CCH's assign students to the morning and afternoon shifts based on their middle school grade point average (GPA). Depending on the quality of the entering class, the administrative authorities in CCH determine a threshold level, 8.5 (out of 10) in most cases, so that students below this threshold are assigned to the afternoon shift. This assignment rule allows us to implement a fuzzy regression discontinuity design (RDD) to identify the effect of being allocated to the afternoon shift, so that we purge our estimates of the negative self-selection that usually plagues this kind of analysis (Van der Klaauw, 2002). To our knowledge, this is the first paper that studies the effect of multiple shifts using an RDD.

This assignment rule may generate different mechanisms through which the school performance of a student may be affected. For instance, the assignment rule amounts to a tracking system uses students' academic ability to separate the students into the two shifts so that each shift is relatively more homogenous in its composition (Hidalgo-Hidalgo, 2011). Tracking systems have two potential effects. On the one hand, it allows professors to target their teaching level to the mean of the group by decreasing the ability gap between the most able student and the least able student. On the other hand, there may be a peer effect within each shift: high ability students may benefit more from their interaction with other high ability students, and low ability students may decrease their performance even further when interacting with other low ability students. This latter effect would increase inequality in performance between the two shifts.

Betts and Shkolnik (1999) conclude that despite the emerging consensus that high-achieving students are benefited in tracking schools and that low performance students are affected, this consensus is based on invalid comparisons. When comparing similar students they conclude that the effect on low-performance students is null and that high-performance students improve. More recently, Duflo, Dupas and Kremer (2011) conducted an experiment in Kenya in which they examined differences between schools with and without tracking and also analyzed the impact for students in different parts of the performance distribution. They find evidence that separation into groups by performance positively affects academic performance for everyone.

Another mechanism that we will investigate is the relative ranking effect. The assignment rule changes the incentives of students who barely made it to the morning shift and those who barely missed the morning shift. The first group of students have the lowest rank, based on their middle school GPA, in their class-shift. The second group of students, those who barely missed the morning shift, have the highest rank in the class-shift. These relative rankings may change the subjective perception that the students have about their own ability, such that an increase in the relative ranking may induce them to exert more effort and thus improve their school performance. Weinhardt and Murphy (2014) measure the long term impact of the ordinal ranking of students in an elementary school. They show that to have a high ranking among peers has a great positive effect on your long-term academic performance.

If the effect of DSS depends on these two mechanisms, as we hypothesize, then the overall effect is a matter of empirical analysis. If peer effects are more important, then we would expect students in the afternoon shift of decrease their performance. If tracking works in favor of all students as in Duflo, Dupas and Kremer (2011), the effect of the afternoon shift will depend on the relative size of the increases in performance. Finally, if relative ranking matters, we would expect students who barely missed the morning shift, and are thus in the afternoon shift, to increase their performance relative to students who barely made it into the afternoon shift.

In our estimates, we used data from administrative records of the CCHs, all of them located in Mexico City, and a socioeconomic survey collected at enrollment in every CCH. In the data we are able to identify each student during the time she remains enrolled in a CCH, so the data has a longitudinal structure. We have data for eight different entering classes between 2005 and 2014. These records have data on grades, high school completion, admission to UNAM, campus of enrollment, class, shift, gender, and many other variables. Each CCH has approximately 3,600 students per entering class.

We find that there are heterogenous effects of the afternoon shift on the dropout rates of men and women, and other groups of interest. In the case of *men*, being in the morning shift *decreases* de probability of dropping out by 12.4 percentage points, whereas for *women* we find an *increase* in the probability of dropping out of 12 percentage points. Our exploration of the mechanisms behind these changes suggests that the effect on men is mostly driven by changes in the relative ranking, whereas the change in women is mostly driven by negative peer effects. We also find that the students who work are the most benefited by their assignment to the afternoon shift: their probability of dropping out decreases by 14.7 percentage points.

In addition, we find that women in the afternoon shift have a higher probability of choosing a science, technology, engineering or mathematics (STEM) major (an 11 percentage point increase), whereas this probability decreases by 19.4 percentage points for male students. We also find that the probability of being admitted to a major in high demand at UNAM decreases by 14.3 percentage points for women, but it increases by 17.1 percentage points for men. We suggest that these gender differences in major selection are a result of a change in the gender composition of each shift.

Our main contribution in this paper is our ability to measure the causal effect of the afternoon shifts in DSS on school performance. Our identification strategy eliminates the selection problem that previous research has not been able to tackle, even if we are only able to identify a local average treatment effect. In addition, we provide evidence of gender differences to negative incentives, peer effects and attitudes towards competition in a non-laboratory setting. Finally, we provide some suggestive evidence that the composition of the group (i.e. proportion of men and women in the group) affects major preferences of individuals.

The rest of the paper is organized as follows. Section 2 describes the research design. In this section we describe the identification strategy, the data used in our estimations and some background about CCHs in order to understand the source of identification. Section 3 presents the main results. Section 4 presents a discussion of our results and concludes the paper.

2. Research design

In this section we will explain our research design. We will first present the identification strategy, then the data that we will use to produce our estimates, and we will also give some background about CCHs in Mexico City.

2.1. Identification strategy

Our objective is to estimate the causal effect of being assigned to the afternoon shift on school performance. If the assignment were randomized, we could estimate the following equation:

$$y_i = \alpha + \beta_1 shift_i + u_i \tag{1}$$

where the outcome variable y_i is equal to 1 if the student dropped out of school and equal to 0 if she successfully concluded high school; $shift_i$ is equal to 1 if the student was assigned to the afternoon shift and equal to 0 if she was assigned to the morning shift; and u_i is a random error. In this case, the parameter measuring the effect would be β_1.

However, as in most of applied research, the afternoon shift is not randomly assigned; that is, there is some form of selection into the different shifts. This selection induces a bias on the estimator of β_1, since there would be some dependence between $shift_i$ and u_i. Hence, $E[shift|u] \neq 0$ and because of the endogeneity of $shift_i$, the OLS estimator will be inconsistent and lack causal interpretation. In our context, we observe that students with higher performance are assigned to the morning shift and the rest to the afternoon shift. There is a clear selection problem. As a result, the probability of dropping out in the morning shift could be different from the probability in the evening shift; however, this is not necessarily the effect of being in the afternoon shift, but a confounded effect of shift, and students observed and unobserved characteristic (such as, their ability).

In order to eliminate the selection bias, we exploit the assignment rule of students to the afternoon shift. After talking to the administrative staff of CCHs, it became very clear to us that the assignment rule was related to middle school GPA: those students with a GPA higher than a cutoff had a greater probability of being assigned to the morning shift. Hence, the assignment methodology creates a discontinuity in the probability of treatment. This suggests that the treatment effect can be consistently estimated using a fuzzy regression discontinuity design (RDD) (Imbens and Lemieux, 2008). The intuition behind this approach is that students who are just above the cut-off point are very similar in observable and unobservable characteristics to those just below it. This allows us to compare the results shown by students who are near the threshold. The identification strategy is based on the assumption that all characteristics that affect the student's results, but the probability of assignment to the afternoon shift, change smoothly over the threshold. As a result, any change in the outcome variable can be solely attributed to enrollment in the afternoon shift.

The fuzzy RDD can be estimated using instrumental variables as long as the order of the smoothing polynomial and the estimation bandwidth used for the first and for the second stages are the same (Van Der Klaauw, 2002). The first and the second stages in this case are:

$$shift_{ict} = \gamma_0 + \gamma_1 I(grade_{ict} < c_{ct}) + f(grade_{ict}) + X'_{ict}\gamma_2 + F_c + F_t + \eta_{ict} \quad (2)$$

$$y_{ict} = \beta_0 + \beta_1 \widehat{shift}_{ict} + f(grade_{ict}) + X'_{ict}\beta_2 + F_c + F_t + u_{ict} \quad (3)$$

where y_{ict} is the outcome variable of interest to the student i, from campus c and class t; $shift_{ict}$ is an indicator equal to 1 if the student is assigned to the afternoon shift and equal to 0 if she is assigned to the morning shift; $I(grade_{ict} < c_{ct})$ is a characteristic function indicating whether the student's middle school GPA ($grade_{ict}$) is below the cutoff c_{ct} of campus c and class t; X_{ict} is a vector of the student's observable characteristics; F_c and F_t are fixed effects for campus and class, respectively; η_{ict} and u_{ict} are random error terms. Finally, $f(grade_{ict})$ is the polynomial control for the regression discontinuity. β_1 is still the parameter of interest, which, under the identification assumptions, constitutes a local average treatment effect. That is, the effect corresponds to those students who would be assigned to the afternoon shift if they had had an average secondary grade below the cut-off, but would be assigned to the morning if they had had an average secondary grade over the cut-off.

In order to determine the degree of the smoothing polynomial $f(grade_{ict})$, we will use the Akaike information criterion. We will estimate the equations above using a bandwidth around the cutoff, which will be determined following Imbens and Kalyanaraman (2008). For robustness, we will also use different bandwidths around the cutoff grade. The aim is to restrict the sample and to compare similar students, identifying the aforementioned local average treatment effect. Finally, since the middle school GPA in our database is rounded to one decimal point, the distribution of the running variable is discrete. Standard errors are, thus, clustered at middle school GPA level as recommended by Lee and Card (2008).

2.2. Data

The data comes from a system of high schools administered by UNAM, the *Colegio de Ciencias y Humanidades* (CCH), which consists of 5 campuses: Naucalpan, Azcapotzalco, Vallejo, East, and South. Each entering class has 3,600 students divided between the morning and afternoon shifts. Our database comes from two sources: administrative data provided by the General Directorate of CCH, and data from a socioeconomic questionnaire applied by the Directorate General of Planning and Evaluation at UNAM.[3] The sample is composed of observations at the student level and covering eight classes in a period from 2005 to 2014. For the purpose of this analysis, all campuses and classes have been combined into a single sample.

The administrative database contains information on the academic record of each student enrolled in the CCH during the period of analysis. It has middle school GPA, high school GPA per semester, number of approved courses, admission to UNAM, and information on school desertion, school expulsion or graduation. This database is

[3] The data was requested through the transparency office of UNAM, No. application F10897.

complemented by a socioeconomic questionnaire, which includes information on the personal and family characteristics of the student such as: type of middle school (public/private), shift in middle school, age, gender, academic habits and attitudes, parents' schooling level, student employment status, and household income, among others.

The restricted sample consists of students between 14 and 16 years old, where 15 years old is the regular entry age.[4] We limit our data to this age range because we presume that students over 16 years of age are under different circumstances which may lead to a bias in our results. The final sample included 73% of the original sample, that is, 96,794 students. Four campuses of the 2007 generation do not have all the required information and were excluded from the dataset. Given the RD design, the sample is limited to students within a bandwidth of 0.40 GPA points around the cutoff.[5] Restricting the sample to observations around the threshold leaves us with 31,372 students.

Table 1 shows descriptive statistics by shift. Panel A presents information for the entire sample. In the morning shift 61% of students are women, average entry age is 15.15 years, average middle school GPA is 9.11, and 11% of the students work. When we compare the statistics of the morning shift with those of the afternoon shift, we observed statistically significant differences in the percentage of women (44% in the afternoon shift) and in average middle school GPA (7.91 in the afternoon shift). The significant differences in those variables suggest that gender and middle school GPA are correlated with shift assignment. Although all the differences are statistically significant, the magnitude of the difference in the rest of the variables does not seem economically significant.

[4] About 10% of those who were admitted were 16 years old at entry.
[5] The optimal bandwidth was determined following Imbens and Kalyanaraman (2011).

2.3. Admission and shift assignment in CCHs

The admission process for the entire public high school system in the metropolitan area of Mexico City is rare and is done on an annual basis. The process is led by the Metropolitan Commission of Public Institutions for Higher Secondary Education (COMIPEMS for its Spanish acronym). Admission is determined based on the score obtained on the standardized admission test and on the preferences of the applicant over the participating institutions. The COMIPEMS then determines which students are admitted to each public high school in Mexico City. The CCHs have acceptance rates ranging from 22% to 48%.[6]

Once the student is admitted to a CCH, it is assigned to one of two shifts. According to the guide to admission to the UNAM high school system, the allocation process is random; that is, assignment to the afternoon shift does not depend on the middle school GPA, gender or age, nor any other characteristic of the student. The allocation is only supposed to balance the number of students per group. However, a detailed analysis of the data shows that the allocation of shift is conditional at least on three observable student characteristics: the middle school GPA, gender and age, with the GPA almost fully determining the shift.

Assignment to the afternoon shift also depends on the characteristics of students being admitted each year. In particular, the cutoff value of middle school GPA may be different for each gender, campus and entering class because it depends on the number of applicants and the distribution of the middle school GPA of those accepted. Also, the assignment rule gives priority to women, which may cause the existence of different cutoff points for men and women. The minimum average grade necessary to be assigned to the morning shift is not known in any case. These differences in the threshold of the assignment rule are taken into account in our RDD estimation. Since the cutoff for each campus-class-gender is not known, we first estimate the cutoff values using the methodology proposed by Card, Mas and Rothstein (2008) and also used by

[6] Based on data from the entering class of 2013, in which 55,190 applicants competed for 18,000 available spaces.

Ozier (2011). Once we have the cutoff values for each class and campus, we re-center the running variable around each cutoff at the gender-campus-class level.

The identification of the cutoff values or discontinuity points is based on structural change analysis (Card *et al*., 2008). The first step is to estimate a regression of the treatment variable (afternoon shift) against a hypothetical discontinuity indicator, which ranges from 7.0 to 10.0 in increments of one-tenth controlling for a flexible polynomial of the running variable (middle school GPA). This procedure is performed independently for each class, campus and gender. For each combination of class, campus and gender, the real point of discontinuity (cut-off point) is the one whose regression produces the highest R-squared.

In general we find that the points of discontinuity are at a GPA of 8.5 (out of 10) for men and women. However, in some years women show some cutoff points at a GPA of 8.9. As supplementary evidence, the same procedure is applied to the whole sample, separating only between men and women. The result shows that the cutoff point is a GPA of 8.5 for men and women. The result is shown in Figure 1.

As we mentioned above, since the cutoff points vary by gender-class-campus, we re-centered the running variable instead of using the actual value of the middle school GPA. There are two alternatives for re-centering the GPA: (1) re-center the running variable using the cutoff at 8.5 for all students, as suggested by the structural change analysis for the whole sample; or (2) re-center the running variable using the corresponding cutoff point applied to each student, according to her gender, class and campus. Figure 2 shows graphically the cutoff point and the discontinuity for both alternatives. As a robustness test, we use both alternative in our estimates of the causal effect of the afternoon shift, but the results are shown only for the second alternative.[7] Panel B of Table 1 presents the descriptive statistics for the discontinuity sample using the second re-centering alternative with a bandwidth of 0.40 points around the cutoff.

[7] The results are robust to both re-centering alternatives.

3. Empirical results

3.1. Testing for the identification assumptions of the RDD

In order to give a causal interpretation to our estimates, the RDD must satisfy some identification assumptions. The main concern is that assignment to the afternoon shift around the threshold is not as if it were randomized; that is, that somehow students know the treatment assignment rule and they are able to manipulate their middle school GPA in order to be assigned to the morning shift, which is arguably the most desirable.

Manipulation of the treatment assignment rule could happen if students could convince their teachers to change their middle school GPA or if they could fine tune their effort in order to get a GPA right above the cutoff GPA in order to be admitted to the morning shift. In our opinion, it is very difficult to manipulate this GPA in order to barely get into the morning shift. This is mostly due because of the following three reasons. First, middle school GPA depends on the effort exerted in school during three years. It is obtained by taking the average of 30 different courses, many of those taught by different teachers. So fine tuning the GPA such that it is right above 8.5 seems like a very unlikely event. Second, as we mentioned in the previous section the guide to admission to UNAM's high schools falsely claims that assignment to the shifts is randomized. Hence, students arguably do not know the treatment assignment rule. And finally, even if students have an idea that they need a certain GPA to get enrolled in the morning shift, we found that the cutoff may vary, thus creating uncertainty on the value of the cutoff for each gender-campus-class combination. As a result, sorting around the threshold may be unlikely.

If there were self-selection around the cutoff, we would expect to find a discontinuity in the distribution of middle school GPA around the threshold required to be enrolled in the morning shift; that is, a disproportionate number of students would sort themselves into being right above the cutoff as compared to those right below the cutoff. Figure 3 shows the distribution of middle school GPA. We do not see any clustering of observations right above the cutoff. In addition, we performed McCrary's (2008) density test to formalize this notion.[8] We found that the discontinuity around the threshold is not statistically significant, and thus we conclude that there is no manipulation of the running variable in our RD design.[9] Another possible source of selection of the students would be if observations with missing values are selected around the threshold. Figure 4 shows the percentage of observations with missing values over the range of the running variable, and we do not observe any discontinuity at the cutoff either.

Another alternative to test the validity of the RDD is to examine if the observable characteristics of the students are continuous around the threshold. Figure 5 presents the graphical evidence on this assumption for age, gender, admission test score, student's employment status, and parents' schooling level. We do not observe any discontinuities in these variables.

The last two columns of Panel B in Table 1 show the difference of the means of the morning and the afternoon shift, and the p-value of a t-test to check whether the difference is statistically significant around the threshold. We observe small differences around the threshold and they are all statistically significant. However, we do not think that any of these differences are big enough in magnitude to be considered economically relevant, especially given the large amount of observations. For instance, the 7 percent difference in the number of women between the morning shift and the afternoon shift amounts to having 126 additional women in the morning shift for each class-campus on average. For these reasons, we will conclude that the treatment and control groups are relatively comparable. In any case, we will also control for observable characteristics in our estimations, and we will also do estimations for

[8] In essence, McCrary's test is a test of the continuity of the running variable density function. The test is an extension of local linear regression with estimates of a smoothed density of the running variable made separately on both sides of the threshold. A statistically significant difference in the intercepts of both regressions would imply that there is a discontinuity in the running variable at the threshold. The test is valid only if manipulation is monotonic; that is, students manipulate their GPA only to get into the morning shift, but not to get into the afternoon shift.

[9] The estimated discontinuity is equal to -0.0023 with a standard error of 0.0155.

subgroups of the population (women, men, and by employment status), which will make the treatment and control groups even more comparable.

3.2. First-stage: discontinuity in the probability of treatment

In Figure 2 we showed that there is a discontinuity in the probability of being assigned to the afternoon shift. Recall we will be re-centering the running variable using all the estimated cutoff levels at the gender-campus-class level. In the graph the magnitude of the discontinuity is of about 0.6, which means that students with a score right below the cutoff decrease the probability of being enrolled in the morning shift by 60 percentage points. Table 2 formalizes this graphical analysis by estimating the first stage in equation (2). Columns 1 to 3 present the results using the whole sample, the next three columns use the sample of women, and the last three columns, the sample of men. We report the estimates without and with the smoothing polynomial on the running variable.[10] We chose a third-degree polynomial with different slopes on either side of the threshold using the Akaike criterion.[11] In addition, we also control for age, gender, parents' years of schooling, student's employment status, dummies of whether the student has children or is married, and characteristics of her middle school (such as whether it was public or private, and the shift in which she was enrolled). We also controlled for fixed effects at the campus and class level.

The estimated discontinuity is robust to the different specifications and subsamples. In our least parsimonious specification, we found that having a score below the cutoff increases the probability of being in the afternoon shift by 61.6 percentage points (pp) for the whole sample, by 66.1 pp for women, and by 55.2 pp for men. The fact that the estimators with and without controls are very similar in the

[10] Recall this polynomial is crucial in the identification strategy.
[11] In fact this polynomial specification is the best fit even for different values of the bandwidth. Test results of robustness with different order polynomials and bandwidths are shown in Table 1 of Appendix A.

different samples supports our conclusion that the treatment and control groups are indeed quite comparable around the threshold.

3.3. Effects of afternoon shift on GPA

Table 3 reports the results on GPA of the first semester, GPA of the last semester, percentage change in the GPA between middle school and the first semester, percentage change in the GPA up to the last semester, probability of high school desertion, probability of admission to majors in high demand at UNAM, and the probability of choosing and being admitted to a STEM major at UNAM. Each coefficient in Table 3 comes from a different regression of the outcome variable on the afternoon shift dummy variable; that is, each coefficient is a different estimate of β_1 in equation (3). The first four columns of Table 3 present four different specifications for the estimates using the whole sample: without and with the smoothing polynomial on middle school GPA, with student's characteristics and background controls, and with fixed effects at the campus and class level. The least parsimonious specification controls for the third-degree polynomial, student's characteristics and background, campus fixed effects, and class fixed effects. Henceforth this will be our preferred specification and this is the one we use for the estimations with the different subsamples in columns 5 to 8 of Table 3.

We will first describe the results of the impact of the afternoon shift on high school grades. Grades range from zero to ten points, with six being the minimum passing grade. High school in CCH consists of six semesters. Panel A of Table 3 presents the results for the GPA of the first semester of high school. When using the complete sample, we can see that the results are robust to the inclusion of the different controls except for the third-degree smoothing polynomial which is necessary for identification in an RDD. We estimate that the effect of the afternoon shift on first semester GPA is between 0.15 and 0.14 points (out of 10). When we look at different subsamples, we find that the effects is slightly larger for men (0.16 points) than for women (0.12 points). We also observe that being in the afternoon shift benefits students who work the most: their grades increase by almost 0.4 points as compared to students who work who are in the morning shift. Students who do not work benefit the least, but still observe a gain in almost 0.1 points as compared to those in the morning shift.[12]

Panel B of Table 3 presents the results for the GPA in the sixth semester (the last one of high school). When considering the whole sample, the results are similar to those in the first semester with an effect of the afternoon shift of about 0.14 to 0.12 points in the GPA. However, the differences between men and women become more acute. In the last semester of high school, men in the afternoon shift exhibit an increase of 0.25 points as compared to men in the morning shift; whereas women only increase their grades by 0.05 points. The differences between employed and non-employed students also widen: employed students gain almost 0.6 points from being enrolled in the afternoon shift, whereas those non-employed only gain 0.05, as compared to those in the morning shift.

When analyzing grades, a possible concern is that teachers curve grades, and thus change the distribution of grades for both morning and afternoon shifts. This practice would render the grades useless to compare performance across shifts. Figure 6 presents a scatterplot of the mean GPA in the first and last semesters with respect to the running variable (the re-centered middle school GPA). If teachers were curving the grades, then the best students in each shift would get 10 or something close to 10 (i.e. an A+) and the rest would be assigned a grade that corresponds to their place in the distribution of grades. If this were true and grades in high school are positively correlated with grades in middle school, in Figure 6 we should then see two increasing lines on each side of the threshold which would be more or less parallel. The discontinuity at the threshold would thus be very large (of about 4 points considering that the minimum passing grade is 6). So the discontinuity in grades that we estimate may be only an artifact due to curved grades. Figure 6 shows that this is not the case. Grades are in fact increasing over the whole range of the running variable implying that teachers are not curving the grades within shifts. In addition, the discontinuity at the

[12] Please keep in mind that the interpretation of all our results are for the sample around the cutoff; that is, those observations within the +/-0.4 bandwidth.

threshold is small in magnitude; as we explained, with a curve, the discontinuity would be much larger.

We now turn our attention to changes in grades between middle school and high school. Figure 7 presents the percentage change of grades in high school (first and sixth semesters) as compared to middle school GPA. We find that all students decrease their grades between middle school and high school on average (the range of the percentage change in the y-axis is always negative). Rosenkranz *et al*. (2014) explain that this drop in grades is due to changes in attendance and effort in the transition from middle school to high school. They argue that students in high school have greater liberties and thus perceive attendance and effort as a choice rather than an obligation.

In addition to a generalized decrease in grades, we also observe that the students with higher grades in middle school exhibit the largest drop in grades as compared to students with lower middle school grades. We observe a discontinuity at the threshold implying that those in the afternoon shift do not drop their grades as much as those in the morning shift. Panels C and D of Table 3 present these results. For the whole sample, we estimate an increase of about 1.3 pp and 1 pp for the first and last semesters, respectively, on the percentage change of grades with respect to middle school GPA. Again, men and employed students exhibit the largest gains from being enrolled in the afternoon shift as compared to those in the morning shift around the threshold level. The gender differences, and working status differences also widen between the first and last semester, as expected.

In sum, we find that students in the afternoon shift display a higher performance, as measured by grades, than students in the morning shift around the cutoff value. Although all students drop their grades in high school, students in the afternoon shift drop their grades by less than students in the morning shift. We presented evidence that this is not due to the curving of grades (which may be the most obvious difference in academic standards). It may be due to a difference in monitoring of students, maybe teachers consider that students in the afternoon shift are a bit more problematic and thus monitor them more strictly. But we cannot offer any evidence on this latter hypothesis.

3.4. Outcome: High school desertion

The outcome of greatest interest to us is high school desertion. This is a more straightforward measure of high school performance that is not subject to the same criticisms as grades. According to the Organization of Economic Cooperation and Development (OECD, 2013), in Mexico more than 40 percent of students between 15 and 19 years old are not enrolled in (high) school. Part of this percentage is due to the students dropping out of the education system before enrolling to high school. Of those who enroll in high school, 15 percent decide to drop out nationwide (as compared to 7 percent in the US). CCH desertion rates are much larger; as we mentioned in the introduction, 38 percent of CCH students drop out.

Figure 8 shows the impact of the afternoon shift on drop-out rates for the whole sample. There is no discernible effect of assignment to the afternoon shift on drop-out rates, but this result is masking some interesting facts. Figure 9 presents the same graph, but divided by subgroups of the population: women, men, employed and non-employed. In this figure, we can identify two groups whose drop-out rates increase when they are enrolled in the afternoon shift: women and non-employed students. In contrast, men and employed students decrease their chances of dropping out when they are enrolled in the afternoon shift.

Panel E of Table 3 presents the formal estimates of those effects. Using the complete sample, we find that students who are just below the cutoff have a higher probability of dropping out than students just above the cutoff of 2.1 pp (Column 4). For women, however, the increase in drop-out rates is of 12 pp and for men the decrease in drop-out rates is 12.4 pp. Employed students also decrease their probability of deserting by 14.7 pp, whereas non-employed students increase their probability by 4.9 pp.

The fact that employed students are the ones who gain the most from being enrolled in the afternoon makes intuitive sense. Working and studying may be more compatible when students are enrolled in the afternoon shift, than when the students are in the morning shift. However, the gender differences in performance attributed to the shift are not as intuitive. Male and female students are taught the same courses and by the same teachers. Unless, teachers treat them differently, then we would not expect to observe these differences a priori. We cannot provide any evidence on how teachers treat their students, since this is unobservable to us. We will look into other hypothesis in order to explain these gender differences.

Our findings so far contradict the common belief that parents have: the afternoon shift is worse than the morning shift. We have found that, in a comparable set of students, students in the afternoon shift have higher grades, drop their high school grades by less as compared to middle school, and men have lower desertion rates, although women have higher drop-out rates. Why is this the case? We have two main hypothesis: a tracking effect and a relative ranking effect.

The treatment assignment rule in our case is almost analogous to a tracking system: the best students are left in the morning shift, while the worst students are enrolled in the afternoon shift on the basis of the middle school GPA. According to Duflo, Dupas and Kremer (2011), tracking has two different effects. First, splitting the students in this fashion makes the groups more homogenous so that teachers can focus their academic level to the average student. Since the groups are more homogenous, the distance between the best and worst students and the average student is lower, and thus everyone can be benefited from more homogenous classes. If this effect dominates, performance would be higher in both the morning and afternoon shift, so the relative effect is unknown. The second effect of tracking refers to peer effects. Given that the best students are all left together, they will benefit from being in contact with the best. In contrast, the worst students are left together and their “bad” behavior may even get worse when surrounded by “bad apples”. If this effect dominates, students in the morning shift would have better performance relative to students in the afternoon shift.

In our design we do not observe a change from the regular system to a tracking system. However, we can exploit the variation in the cutoff values to shed some light on the effect of having more homogenous groups. A lower value of the cutoff would imply that the afternoon shift becomes more homogenous relative to the morning shift, and thus performance in the afternoon shift should increase relative to the morning shift.

There would also be a larger negative peer effect in the afternoon because there would be even less “good apples”. Thus, *with a lower value of the cutoff: if the homogeneity effect dominates, we should observe that the afternoon shift has better performance than the morning one*. In contrast, a higher value of the cutoff would imply that the afternoon shift is more heterogenous relative to the morning shift, and hence performance in the afternoon should fall relative to the morning. The negative peer effects in the afternoon are now attenuated by admitting more “good apples”. Then, *with a higher value of the cutoff: if the heterogeneity effect dominates the peer effect, then we should observe that the afternoon shift performs worse than the morning shift*.

Recall that the cutoff value varies at the gender-campus-class level. Using the structural change analysis, we found two different cutoff values for women: 8.4 and 8.9; and two different cutoff values for men: 7.9 and 8.4. Table 4 presents the results of estimating the effect of the afternoon shift on desertion separately for each cutoff value. We find that an increase in the value of the cutoff for women leads to an increase in the performance of the afternoon shift: women admitted to the afternoon shift with an 8.9 cutoff have a lower desertion rate than women admitted to the afternoon shift with an 8.4 cutoff. Hence we can conclude that in the case of women the peer effect is the dominant one. In contrast, men with a lower cutoff rate decrease their desertion rates even more, and thus the homogeneity effect dominates in the case of men.

Another interpretation of our results could be that being assigned to the afternoon shift represents a negative incentive for the student, since the morning shift is more desirable. Our results contribute to the literature on gender differences in the response to incentives, where previous research finds that women are more responsive to positive incentives than men (Lindo, Sanders y Oreopoulos, 2010). In this paper, we find that men respond with a higher performance (a lower desertion rate) to the negative incentive (afternoon shift), whereas women respond with a lower performance (higher desertion rate) to the same negative incentive.

It is also important to notice that even when both men and women face the same cutoff, the sign of the afternoon shift effect on desertion is different across genders. This is where we think the second mechanism is important, the relative ranking effect. The literature on gender differences in the preferences for competition may shed some light on the gender gap that we find. According to the experiments conducted by Gneezy, Niederle and Rustichini (2003), and Niederle and Vesterlund (2007), when the environment is more competitive, men increase their performance, but women do not, especially if women have to compete against men. This gender difference in the attitudes towards competition may explain the gender gap in performance in the afternoon shift.

The assignment rule to the afternoon shift mechanically changes the relative ranking that the students have with respect to their peers. Say the cutoff is 8.5 for everyone, so that a student with 8.5 is assigned to the morning, but a student with 8.4 is assigned to the afternoon. A student who has a GPA of 8.4 is ranked in the middle of the whole distribution of students, just below someone with an 8.5, and both students were average students in their respective middle schools. But if we apply the treatment rule of assignment, the student with an 8.5 is suddenly among the worst of the morning shift, and the student with an 8.4 is among the best of the afternoon shift. These changes in the relative rankings of both students may have a psychological effect in the student. Murphy and Weinhardt (2014) claim that self-confidence may be the mechanism that better explains their findings on the impact of ordinal ranking on school performance. Other mechanisms could be competitiveness, self-assessments of ability, or an environment that favors certain ranks (i.e. teaching directed to the top of the class).

In order to test for the effect of relative ranking, we will estimate the following equation:

$$y_{ict} = \alpha + \beta_1 ranking_{ict} + \beta_2 GPA_{ict} + X'_{ict}\beta_3 + F_c + F_t + u_i, \tag{4}$$

where y_{ict} is a dummy for desertion of student i, in campus c, and class t; $ranking$ is the student's ordinal ranking in accordance to her middle school GPA, her shift, campus and class;[13] GPA is the student's middle school GPA; X is a vector of student's characteristics; and F_c and F_t are campus and class fixed effects, respectively. We would

[13] In order to facilitate the interpretation of the ranking effect, we standardized the ranking to a range between 0 and 1, where 0 is the worst student and 1 is the best student.

thus expect $\beta_1 < 0$; that is, being better ranked among their peers, leads the students to a lower desertion rate.

We present the results of the estimates in Table 5. In general we observe that both men and women in all shifts benefit from being better ranked. However, the estimates from the afternoon shift are larger in magnitude than the estimates of the morning shift. Furthermore, men exhibit an effect of ranking 58 percent higher than women in the afternoon shift, but not in the morning shift. Recall that the best students in the morning shift do not really see a change in their relative rank as compared to how they did in middle school. However, the best students in the afternoon shift do experience a change in their ordinal rank. We think that this relative change and the subsequent boost in their motivation (self-assessment or self-confidence) may be driving these results.

Figure 10 shows the predicted desertion probability for students at the threshold using the estimates from equation (4); that is, we set the ordinal ranking to 1 for afternoon students, and 0 for morning students, the re-centered middle school GPA is set at zero (the cutoff), and all other characteristics are evaluated at the mean of the sample. Our objective here is to see if the relative ranking effect helps explain the treatment effect on desertion. Once we consider ranking, the difference in desertion rates between the afternoon and the morning shift is now positive for men and equal to 2.6 pp, and for women this differences is of 5.2 pp. This suggests that most of the estimated effect of the afternoon shift for men is due to a relative ranking effect. However, women do not respond as much to the relative ranking. This gender difference in the response to relative ranking is in accordance to Murphy and Weinhart's (2014) findings.

3.5. College admission (UNAM)

The students who successfully complete high school at CCH earn their right to be admitted to UNAM for college. This implies that they do not participate in the very competitive admission process that students from non-UNAM high schools have to undergo. However, admission to certain high demand majors is not guaranteed, since it depends on high school performance.

Panel F in Table 3 presents the effect of afternoon shift on the probability of being admitted to a high demand major at UNAM (top 10).[14] When we look at the complete sample, we find that the afternoon shift leads to a drop of 2.2 pp in the probability of being admitted to a high demand major. This result again masks important differences between men and women: whereas women exhibit a lower probability of being admitted to one of those majors (by 14.3 pp), men present a higher probability of admission (by 17.1 pp) as compared to students in the morning shift. This effect is in accordance with previous results since we have found that men at have higher academic performance when compared to men in the morning; hence, they are better enabled to being accepted to a more competitive major. Finally, Panel G in Table 3 reports the effect on the probability of being admitted to STEM majors at UNAM. We find that for the overall sample, the effect of the afternoon shift on this probability is negative, implying a drop in 1.1 pp. However, we find that women in the afternoon shift increase their chances of being accepted to a STEM major by 11 pp, while men decrease their chances by 19.4 pp as compared to students in the morning shift. Figure 11 presents the graphical representation of these results.

How can we explain these gender differences in the acceptance rates to the different types of majors? In Table 6 we present the percentage of women admitted to the top 10 majors in demand (Panel A) and to the STEM majors (B). We see that a high percentage of women are admitted to high demand majors (63 percent), whereas a low percentage of 39 percent are admitted to STEM majors. Razo (2008) describes STEM majors as typically masculine. The author argues that one of the many factors that influence women in their major choice is the opinion of their peers, besides the opinion of family members and personal preferences. Only 39 percent of students in the morning shift are men, whereas 56 percent of students are men in the afternoon shift.

[14] We consider the major with higher demand in 2011, which were: law, medicine, psychology, architecture, dentistry, communication sciences, biology, management, accountancy, and veterinary. These high demand majors change little over time.

So it is possible that having more male peers is steering more women into STEM majors than into the high demand majors which seem to be female-dominated. Our results on desertion suggested that females in the afternoon shift are more influenced by their peers. This influence may go beyond a negative effect on desertion rates, and into the college major choice.

4. Discussion and conclusions

There is some concern that, even though double-shift schooling (DSS) systems are an effective way to increase education supply at low cost, they could be increasing the inequality of opportunities across students in the morning and afternoon shifts. It is well known that the worst students tend to be enrolled in the afternoon shift, thus DSS systems may widen the gap between the students in both shifts. Knowing the effect of DSS on students' performance is thus very important to assess the overall costs of DSS systems. However, it is very difficult to estimate the effect of being assigned to the afternoon shift on schooling performance precisely because of those negative selection of students.

In this paper, we solve for this estimation challenge by exploiting the assignment rule to the afternoon shift implemented in the CCH system of UNAM's high schools. The assignment rules induce students with a high GPA in middle school to be assigned to the morning shift with a higher probability. The assignment rule uses a cutoff GPA that varies by gender, campus, and class depending on the characteristics of each incoming class. We thus use this assignment rule to implement a fuzzy regression discontinuity design.

Our results do not support the common beliefs that the afternoon shift is intrinsically worse. We find that students in the afternoon shift have better grades than students in the morning shift around the cutoff. The gains in grades are larger for men than for women, and for employed students than for non-employed students. We also provide evidence for other measures of performance such as desertion, and admission to different subsets of UNAM majors. In these other variables the results were even more interesting because we found large and opposing effects for men and women.

Women in the afternoon shift desert school with a higher probability than women in the morning shift; whereas men desert less than their male peers in the morning shift. We advance two mechanisms on why this may be the case: a tracking effect and a relative ranking effect. First, the tracking effect results from splitting the students on the basis of middle school GPA. The tracking effect is composed of two opposing relative effects: the effect of having a more homogenous group that facilitates teaching to the mean, and the peer effect. We find that men tend to benefit from having more homogenous groups in the afternoon shift, but women are negatively affected from having worse peers in the afternoon shift.

The second mechanism that we test is the relative ranking effect. The assignment rule to the afternoon shift automatically changes the relative ranking of students around the threshold level. Those right above the threshold end up in the morning shift, but they are the worst among their peers; while, those right below the threshold end up in the afternoon shift, but they are the best among their peers. These changes in the relative ranking may change the self-image of students, the self-confidence or the self-assessment of their capabilities. Whichever the case, research has found that men respond more to ordinal ranking than women (Murphy and Weinhart, 2014), and we confirm those results in this paper. Men decrease their desertion rates more when they are ranked relatively higher, and especially if they are in the afternoon shift. Although women also respond positively to ranking, we do not find large differences across shifts, which is what really matters in our research design. We still need to do further research to pinpoint the underlying mechanism behind our results.

Finally, we looked into the effect of being enrolled in the afternoon on admission to different subsets of majors at UNAM, where CCH students who successfully complete high school have a reserved space. We analyzed the effect on being admitted to the top ten majors in demand, which are arguably the most difficult to get into. We found yet again a difference between men and women: women in the afternoon shift have a lower chance on being admitted to a high demand major, while men have a higher chance of admission. These results are in accordance to our previous findings. However, when we look at STEM majors, now women in the afternoon shift have a higher chance to be admitted to a STEM major than women in the morning shift, and the opposite is true of men. If women are more influenced by their peers, as our results on desertion suggest, then women in the afternoon shift, who have more male peers than those in the morning shift, may change their preferences towards more masculine majors such as the STEM majors.

Given our results, our paper contributes to the literature on the impact of education policies that use double- or multiple-shift schooling in order to increase schooling supply. Our results contrast with those in Sagyndykova (2013), but she analyzes students in middle school who may still perceive their schooling as an obligation. More interestingly, we also contribute to the literature on the gender differences in the response to incentives, competition, and peers.

There are two main drawbacks in our analysis. First, we could not get data on the quality of teacher, instructional time, and quality of instruction. We talked to a CCH teacher who declared that usually the afternoon shift has exactly the same teachers than the morning shift. If anything, we would expect the teachers to be more tired in the afternoon than in the morning, but this would point to worse quality of instruction, which is not consistent with our results. The second drawback is that our research design only allows us to estimate a local average treatment effect (LATE). We may not be able to generalize our conclusions to those individuals outside of the bandwidth that we used in our analysis. However, we do resolve the problem of having a treatment and a control group which are comparable, which is much more than previous literature has achieved.

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Table 1. Descriptive statistics

Variable	Morning shift Mean	Morning shift S.D.	Afternoon shift Mean	Afternoon shift S.D.	Difference	P-value
Panel A. Full Sample						
Characteristics						
Female	0.61	0.49	0.44	0.50	0.17	0.000
Age	15.15	0.41	15.30	0.49	-0.14	0.000
Middle school GPA	9.11	0.51	7.91	0.51	1.20	0.000
Diagnostic entrance test	6.73	0.73	6.45	0.63	0.28	0.000
Employment status	0.11	0.31	0.17	0.37	-0.06	0.000
Years of schooling: Mother	10.57	3.54	10.78	3.48	-0.21	0.000
Years of schooling: Father	10.85	4.19	11.03	4.21	-0.18	0.000
Household income*	2.43	1.27	2.53	1.29	-0.10	0.000
Outcomes						
High school GPA: 1st semester	8.06	1.01	7.17	1.07	0.88	0.000
High school GPA: Last semester	8.22	0.92	7.30	1.01	0.91	0.000
Admitted: Top 10 majors UNAM	0.46	0.50	0.29	0.45	0.17	0.000
Drop-out rate	0.36	0.43	0.50	-0.27	0.00	0.000
Observations	54,906		41,888		96,794	
Panel B. Discontinuity Sample +/- 0.4						
Characteristics						
Female	0.59	0.49	0.52	0.50	0.07	0.000
Age	15.16	0.41	15.26	0.47	-0.10	0.000
Middle school GPA	8.73	0.30	8.39	0.26	0.34	0.000
Diagnostic entrance test	6.70	0.70	6.38	0.59	0.32	0.000
Employment status	0.12	0.32	0.15	0.35	-0.03	0.000
Years of schooling: Mother	10.81	3.51	10.56	3.47	0.25	0.000
Years of schooling: Father	11.06	4.22	10.90	4.14	0.16	0.000
Household income*	2.52	1.30	2.43	1.24	0.09	0.000
Outcomes						
High school GPA: 1st semester	7.68	0.96	7.47	1.04	0.21	0.000
High school GPA: Last semester	7.87	0.88	7.61	0.98	0.26	0.000
Admitted: Top 10 majors UNAM	0.41	0.49	0.37	0.48	0.04	0.000
Drop-out rate	0.22	0.41	0.32	0.47	-0.11	0.000
Observations	18,030		13,342		31,372	

Notes: Panel B shows descriptive statistics restricting the full sample to 0.4 points arround the cutoff point of the assignation variable determined for each class/campus/gender.
*Definition of household income vairable is as follows: Categorical Variable = 1: 1-2 minimum wages, 2: 3-4 minimum wages, 3: 5-6 minimum wages.

Table 2. Estimated discontinuity (first stage)

OUTCOME: Afternoon Shift									
SAMPLE RESTRICTION:		Full			Female			Male	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ind(GPA<0)	0.636***	0.600***	0.615***	0.639***	0.644***	0.661***	0.630***	0.548***	0.552***
	[0.007]	[0.000]	[0.000]	[0.007]	[0.000]	[0.003]	[0.010]	[0.000]	[0.002]
GPA		0.632***	0.716***		0.861***	0.934***		0.350***	0.348***
		[0.000]	[0.012]		[0.000]	[0.011]		[0.000]	[0.027]
GPA x Ind(GPA<0)		-1.708***	-1.608***		-1.489***	-1.257***		-1.894***	-1.986***
		[0.000]	[0.024]		[0.000]	[0.066]		[0.000]	[0.035]
GPA^2		-3.500***	-4.037***		-4.366***	-4.851***		-2.428***	-2.718***
		[0.000]	[0.063]		[0.000]	[0.095]		[0.000]	[0.151]
GPA^2 x Ind(GPA<0)		-1.750***	-0.287**		1.869***	4.060***		-5.684***	-6.164***
		[0.000]	[0.062]		[0.000]	[0.467]		[0.000]	[0.176]
GPA^3		4.988***	6.012***		6.155***	6.996***		3.525***	4.545***
		[0.000]	[0.099]		[0.000]	[0.184]		[0.000]	[0.247]
GPA^3 x Ind(GPA<0)		-12.500***	-12.150***		-8.664***	-6.780***		-16.186***	-18.890***
		[0.000]	[0.225]		[0.000]	[0.560]		[0.000]	[0.287]
Constant	0.119***	0.099***	-1.522***	0.109***	0.071***	-1.508**	0.133***	0.136***	-1.712***
	[0.005]	[0.000]	[0.278]	[0.004]	[0.000]	[0.284]	[0.008]	[0.000]	[0.249]
Other controls:									
Picewise polynomial order		Cubic	Cubic		Cubic	Cubic		Cubic	Cubic
Controls			Y			Y			Y
Fixed effects			Y			Y			Y
R^2	0.41	0.41	0.44	0.42	0.42	0.46	0.39	0.39	0.47
Observations	31,372	31,372	31,372	17,458	17,458	17,458	13,914	13,914	13,914

Notes: Standard errors, clustered at the GPA level, are in brackets. GPA has been re-centered at the cutoff. Controls, when indicated, include age, gender (if the sample is not split by gender), parents' education levels, employment status, student has children, student married, and private/public secondary school indicator. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3. Estimated effect of assignation to the afternoon shift

SAMPLE RESTRICTION:	Full	Full	Full	Full	Female	Male	Employed	Non-employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. 1st Semester GPA								
Afternoon shift	-0.345***	0.154***	0.143***	0.142***	0.118***	0.162***	0.395***	0.095***
	[0.097]	[0.000]	[0.003]	[0.003]	[0.004]	[0.007]	[0.023]	[0.003]
Panel B. 6th Semester GPA								
Afternoon shift	-0.402***	0.139***	0.122***	0.130***	0.045***	0.255***	0.563***	0.050***
	[0.099]	[0.000]	[0.002]	[0.003]	[0.003]	[0.007]	[0.024]	[0.004]
Panel C. Percent Change in GPA at 1st Semester								
Afternoon shift	0.028***	0.014***	0.013***	0.015***	0.008***	0.021***	0.043***	0.009***
	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.003]	[0.000]
Panel D. Percent Change in GPA at 6th Semester								
Afternoon shift	0.022***	0.012***	0.010***	0.013***	-0.001***	0.032***	0.062***	0.004***
	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.003]	[0.000]
Panel E. Dropout probability								
Afternoon shift	0.132***	0.008***	0.018***	0.021***	0.120***	-0.124***	-0.147***	0.049***
	[0.025]	[0.000]	[0.002]	[0.001]	[0.002]	[0.004]	[0.010]	[0.002]
Panel F. Probability of Admission to High Demand Major in UNAM								
Afternoon shift	-0.082***	-0.020***	-0.025***	-0.022***	-0.143***	0.171***	0.160***	-0.052***
	[0.022]	[0.000]	[0.002]	[0.002]	[0.003]	[0.004]	[0.012]	[0.002]
Panel F. Probability of Admission to Hard Sciences and Engineering Major in UNAM								
Afternoon shift	0.132***	-0.027***	-0.016***	-0.011***	0.110***	-0.194***	-0.227***	0.023***
	[0.025]	[0.000]	[0.002]	[0.002]	[0.002]	[0.005]	[0.011]	[0.003]
Other controls:								
Picewise polynomial order		Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Controls			Y	Y	Y	Y	Y	Y
Fixed effects				Y	Y	Y	Y	Y
Observations	31,372	31,372	31,372	31,372	17,458	13,914	4,073	27,299

Notes: Each coefficient reprents an estimate from a different regression for each outcome variable. Standard errors, clustered at the GPA level, are in brackets. GPA has been re-centered at the cutoff. Controls, when indicated, include age, gender (if the sample is not split by gender), parents' education levels, employment status, student has children, student married, and private/public secondary school indicator. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4. Estimated effect on dropout by gender and cutoff

OUTCOME: Dropout				
SAMPLE RESTRICTION:	Female		Male (Campus 3)	
CUT-OFF:	8.4	8.9	7.9	8.4
	(1)	(2)	(3)	(4)
Afternoon shift	0.247***	-0.108***	-1.144***	-0.093***
	[0.002]	[0.006]	[0.080]	[0.013]
GPA	1.355***	-0.560***	9.005***	-0.119
	[0.042]	[0.049]	[0.939]	[0.147]
Age	-0.001	0.014	0.079	0.033*
	[0.013]	[0.013]	[0.072]	[0.015]
Employment status	0.045***	0.031	0.169*	0.058*
	[0.014]	[0.017]	[0.071]	[0.023]
Constant	0.225	0.100	-0.324	0.267
	[0.186]	[0.187]	[1.009]	[0.242]
Other controls:				
Picewise polynomial order	Cubic	Cubic	Cubic	Cubic
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	9,232	8,226	380	2,649

discontinuity. Controls include parents' education levels, student has children, student married, and private/public secondary school indicator. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5. Estimated effect of ranking on dropout

OUTCOME: Dropout				
SAMPLE RESTRICTION:	Female		Male	
SHIFT:	Afternoon	Morning	Afternoon	Morning
	(1)	(2)	(3)	(4)
Ranking	-0.031*	-0.012*	-0.049***	-0.015
	[0.015]	[0.006]	[0.015]	[0.009]
GPA	-0.146***	-0.102***	-0.107***	-0.116***
	[0.030]	[0.013]	[0.032]	[0.018]
Age	0.013	0.026***	0.035***	0.049***
	[0.007]	[0.005]	[0.007]	[0.007]
Employment status	0.035**	0.032***	0.026**	0.037***
	[0.011]	[0.007]	[0.008]	[0.007]
Constant	1.439***	0.693***	0.918***	0.486*
	[0.272]	[0.142]	[0.266]	[0.190]
Other controls:				
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	18,628	33,520	23,260	21,386

discontinuity. Controls include parents' education levels, student has children, student married, and private/public secondary school indicator. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6. Percentage of women admitted by major (UNAM)

Major	Percentage of women	No. of students
Panel A. High demand majors (Top 10)		
Global	**0.63**	**37,777**
Law	0.60	7,506
Medicine	0.71	5,521
Psychology	0.77	5,123
Dentistry	0.69	3,633
Architecture	0.44	3,474
Biology	0.58	2,896
Business Administration	0.57	2,748
Communications Science	0.67	2,420
Accounting	0.49	2,274
Panel B. STEM majors		
Global	**0.39**	**2,274**

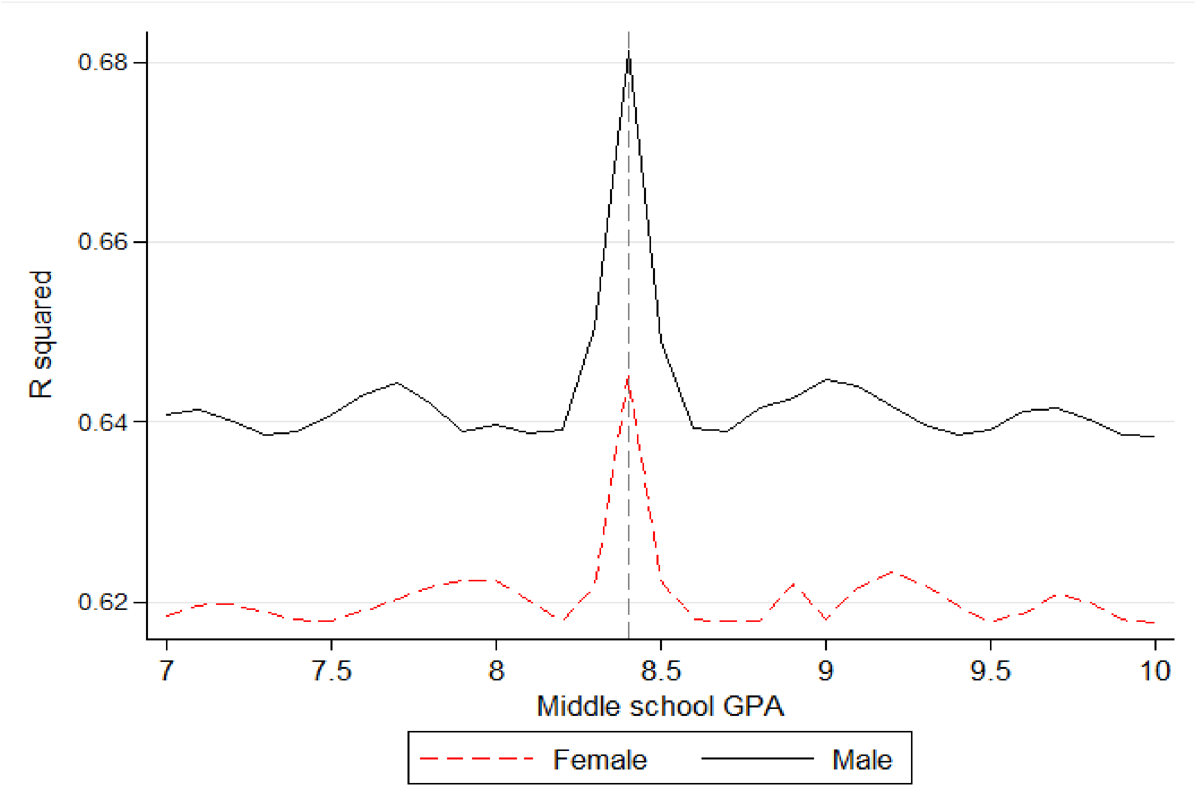
Note: The only high demand major in STEM majors is Architecture.

Table A1. Robustness: Alternative bandwidth

OUTCOME: Dropout					
SAMPLE RESTRICTION:			Full		
BANDWIDTH:	+/- 0.4	+/- 0.2	+/- 0.8	+/- 0.4	+/- 0.4
	(1)	(2)	(3)	(4)	(5)
Afternoon Shift	0.021***	0.008***	0.01	0.002	0.007
	[0.001]	[0.001]	[0.007]	[0.008]	[0.006]
GPA	0.286***	-0.107***	-0.124**	-0.205***	-0.091
	[0.016]	[0.005]	[0.046]	[0.015]	[0.053]
GPA x Ind(GPA<0)	-0.701***	-0.139***	-0.065	0.018	-0.167**
	[0.025]	[0.006]	[0.061]	[0.017]	[0.057]
GPA^2	-2.557***		-0.304		-0.283*
	[0.090]		[0.160]		[0.130]
GPA^2 x Ind(GPA<0)	1.412***		0.305		0.101
	[0.085]		[0.187]		-0.147
GPA^3	3.798***		0.331*		
	[0.150]		[0.142]		
GPA^3 x Ind(GPA<0)	-5.420***		-0.403*		
	[0.248]		[0.173]		
Female	-0.064***	-0.064***	-0.059***	-0.064***	-0.064***
	[0.006]	[0.008]	[0.004]	[0.006]	[0.006]
Age	0.019*	0.008	0.027***	0.021**	0.020**
	[0.007]	[0.004]	[0.006]	[0.007]	[0.007]
Employment status	0.039***	0.039**	0.036***	0.040***	0.040***
	[0.009]	[0.015]	[0.005]	[0.009]	[0.009]
Constant	0.091	0.267***	-0.062	0.084	0.083
	[0.112]	[0.052]	[0.087]	[0.113]	[0.113]
Other controls:					
Picewise Polinomial Order	Cubic	Cubic	Cubic	Linear	Quadratic
Controls	Y	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y
AIC	36184.1			36243.67	36226.72
Observations	31,372	15,840	61,986	31,372	31,372

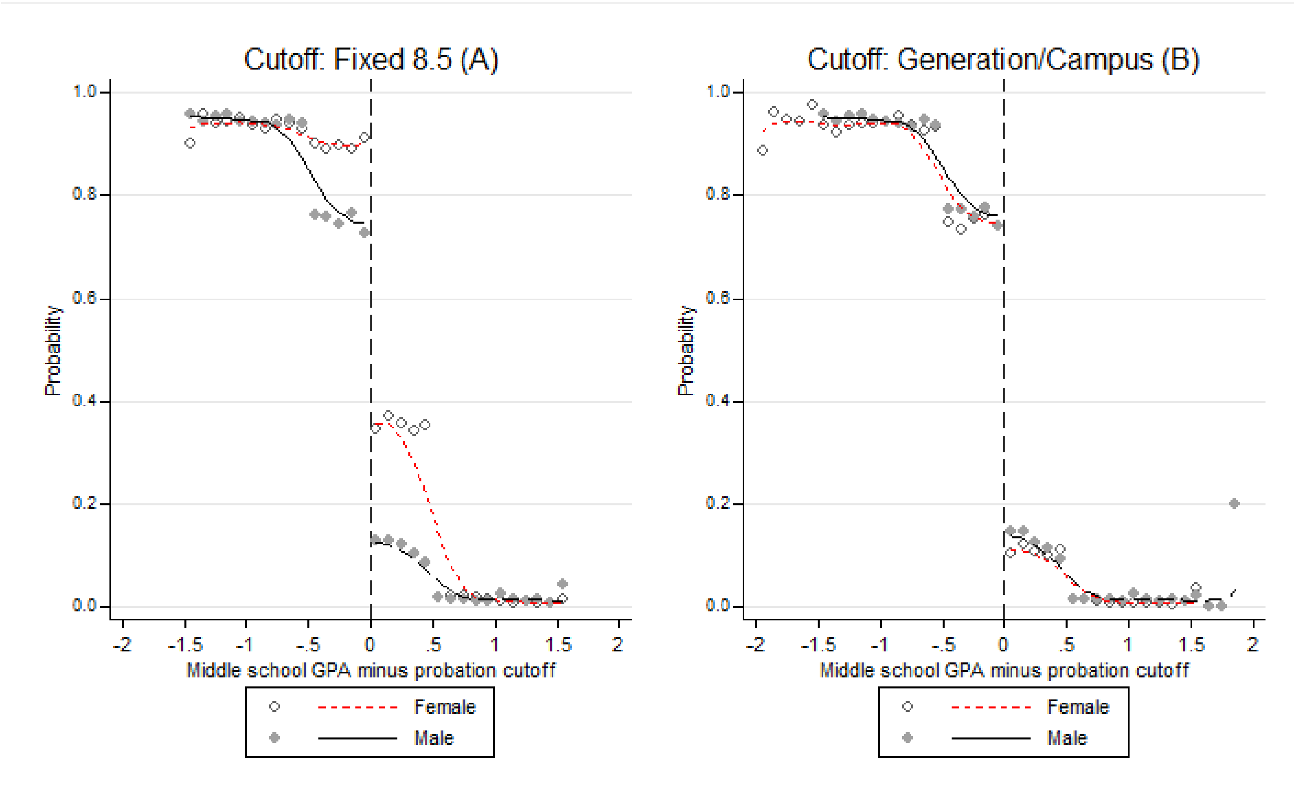
Notes: Standard errors, clustered at the GPA level, are in brackets. GPA has been re-centered at the discontinuity. Controls include parents' education levels, student has children, student married, and private/public secondary school indicator. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 1: Structural change analysis



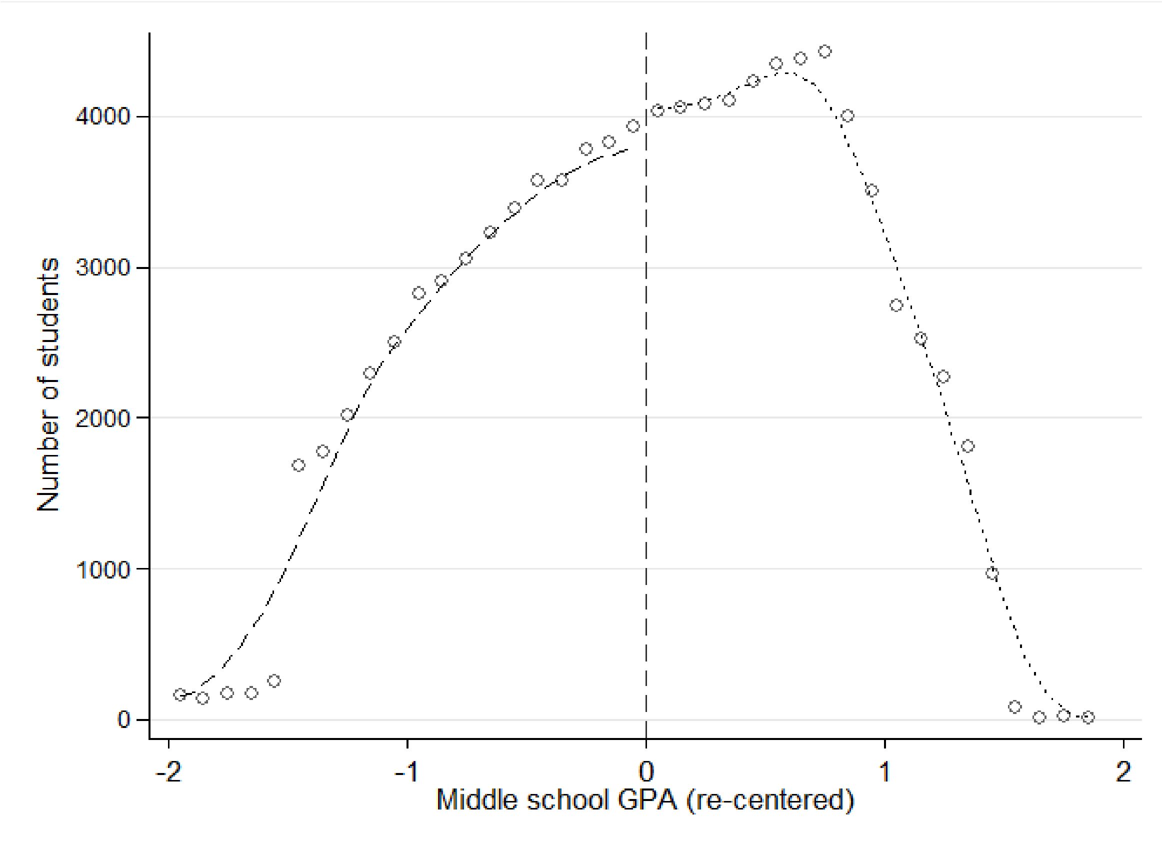
Notes: Estimations based on the methodology used by Card, Mas, y Rothstein (2008).

Figure 2: Probability of assignment to the afternoon shift



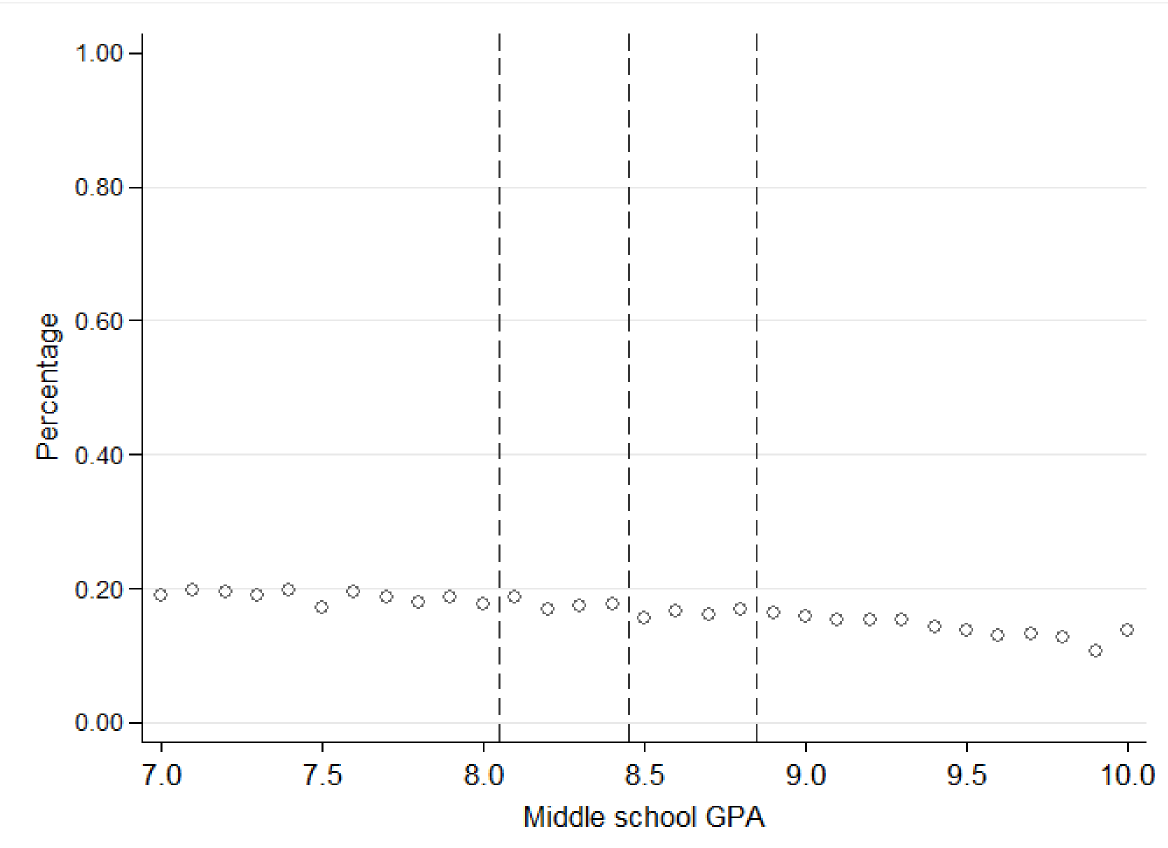
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The solid and dotted lines are predicted from local linear regressions with a bandwidth of 0.4.

Figure 3: Distribution of students relative to the cutoff



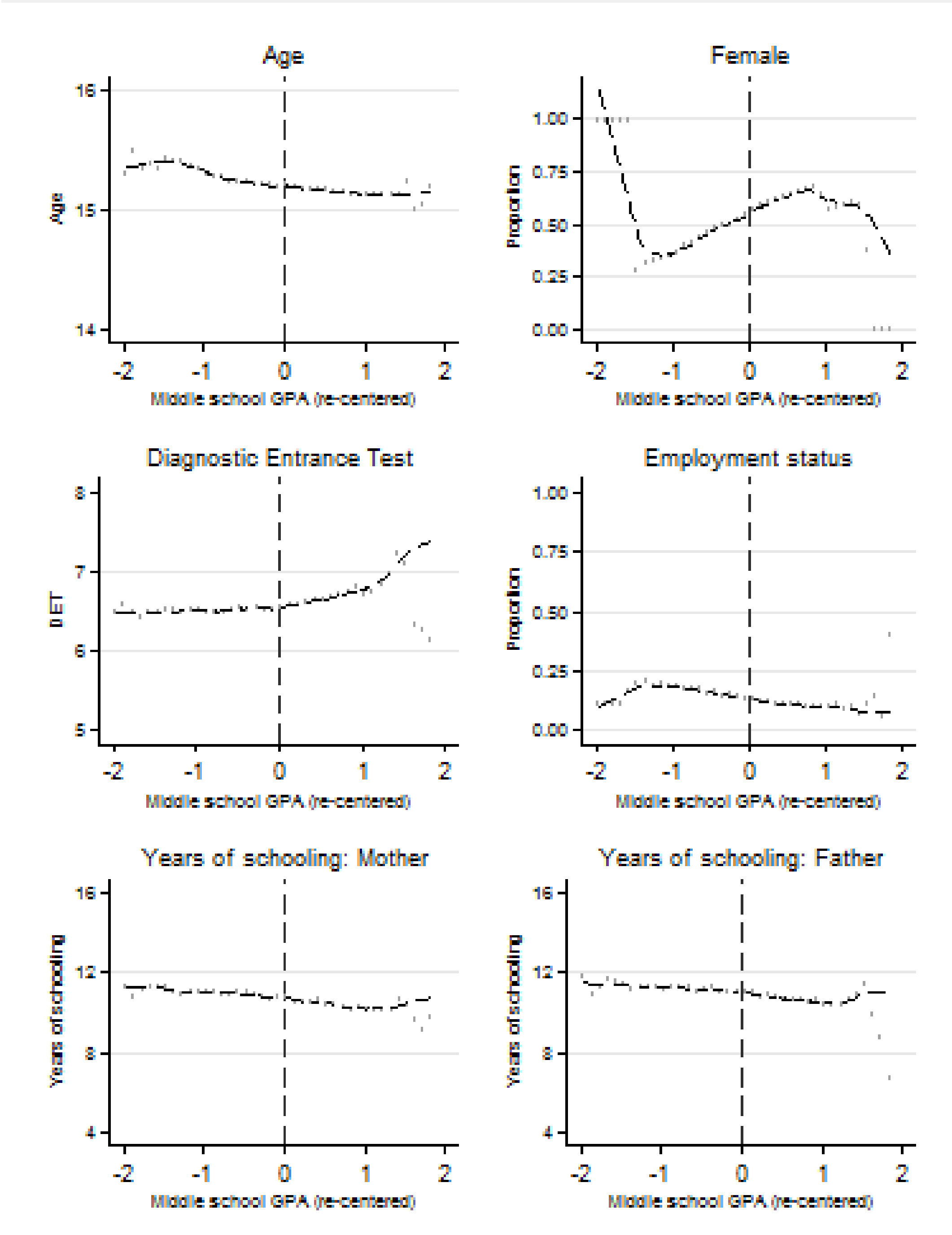
Notes: Each circle represents the number of students in an interval of 0.1 around the central point. The dotted line is predicted from a local linear regression with a bandwidth of 0.4.

Figure 4: Percentage of observations with mising values



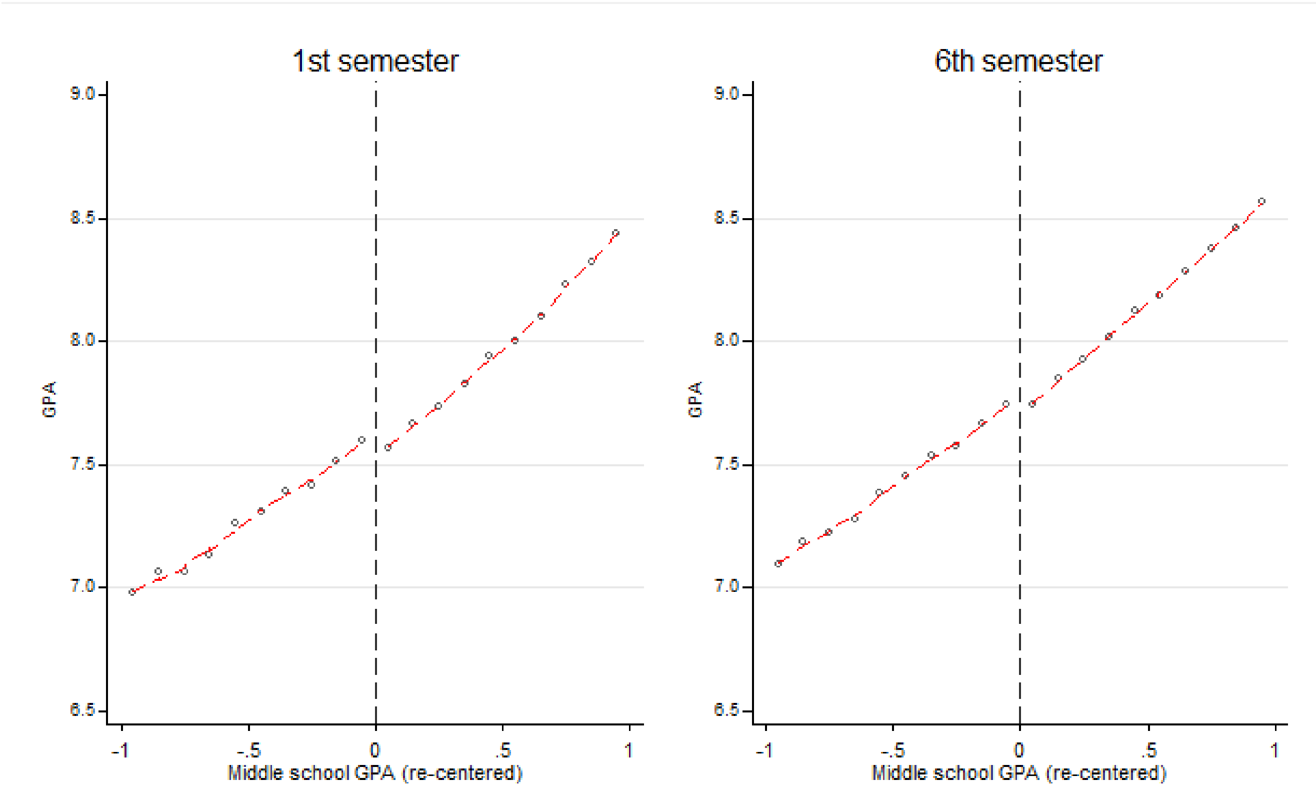
Notes: Each circle is the percent of observations with missing values in an interval of 0.1 around the central point.

Figure 5: Continuity in observable characteristics



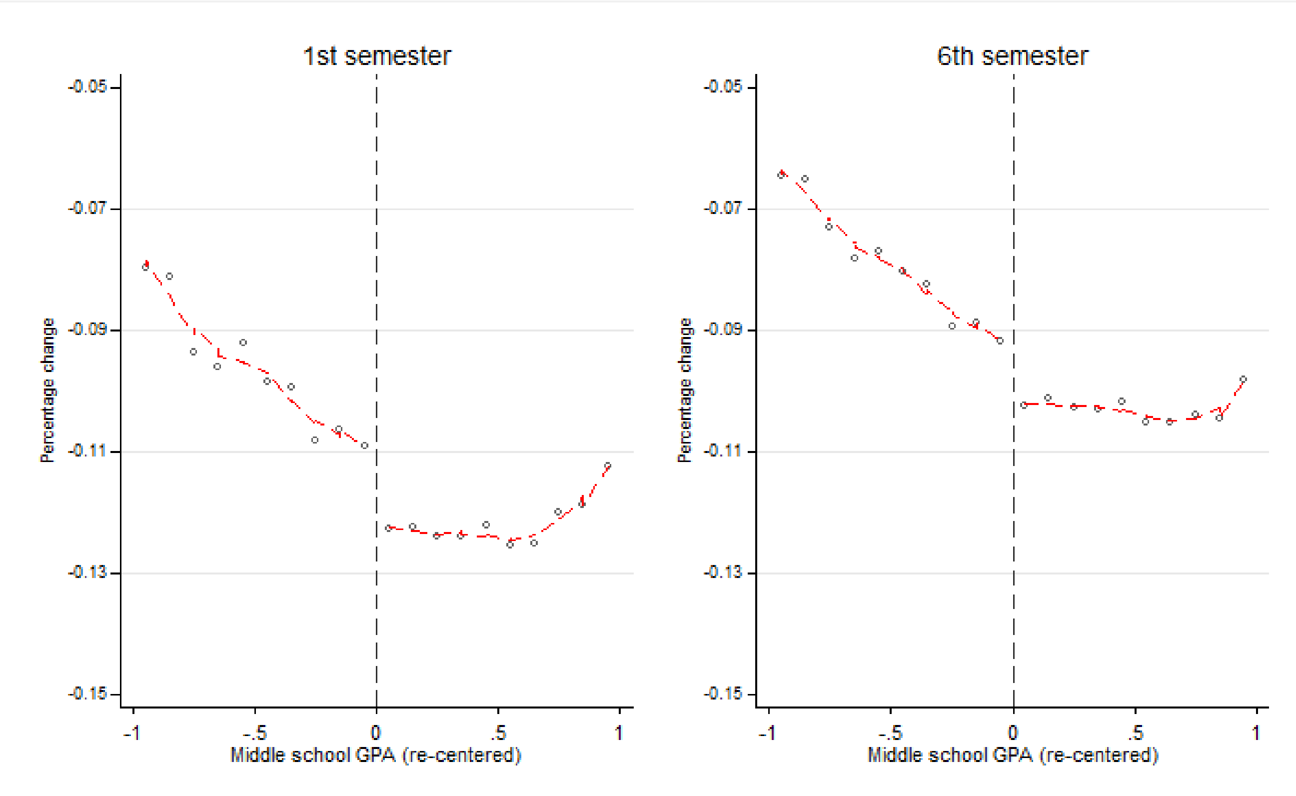
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted lines are predicted from local linear regressions with a bandwidth of 0.4.

Figure 6: Discontinuity in high school GPA



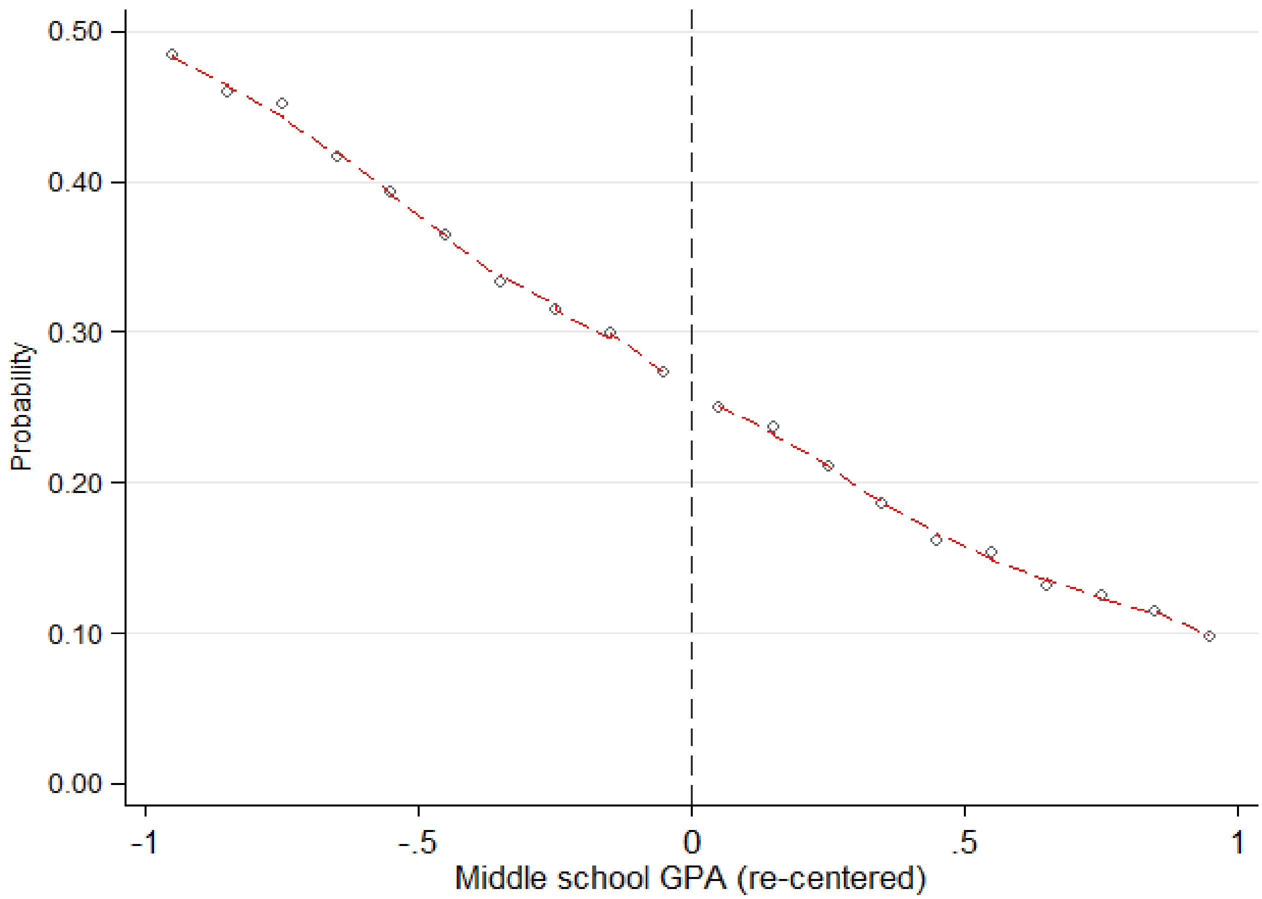
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted lines are predicted from local linear regressions with a bandwidth of 0.4.

Figure 7: Percentage change in high school GPA



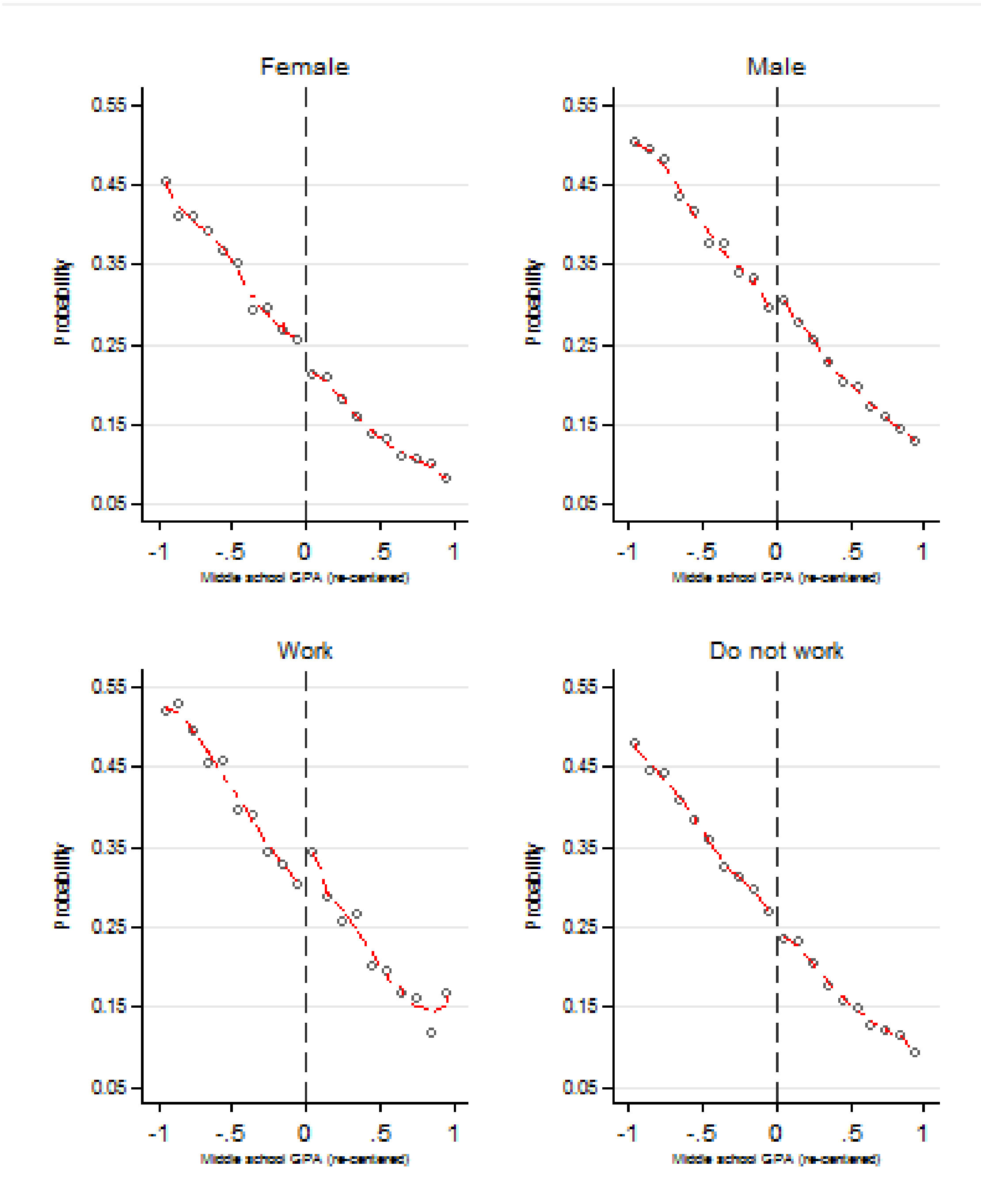
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted lines are predicted from local linear regressions with a bandwidth of 0.4.

Figure 8: Discontinuity in the desertion probability



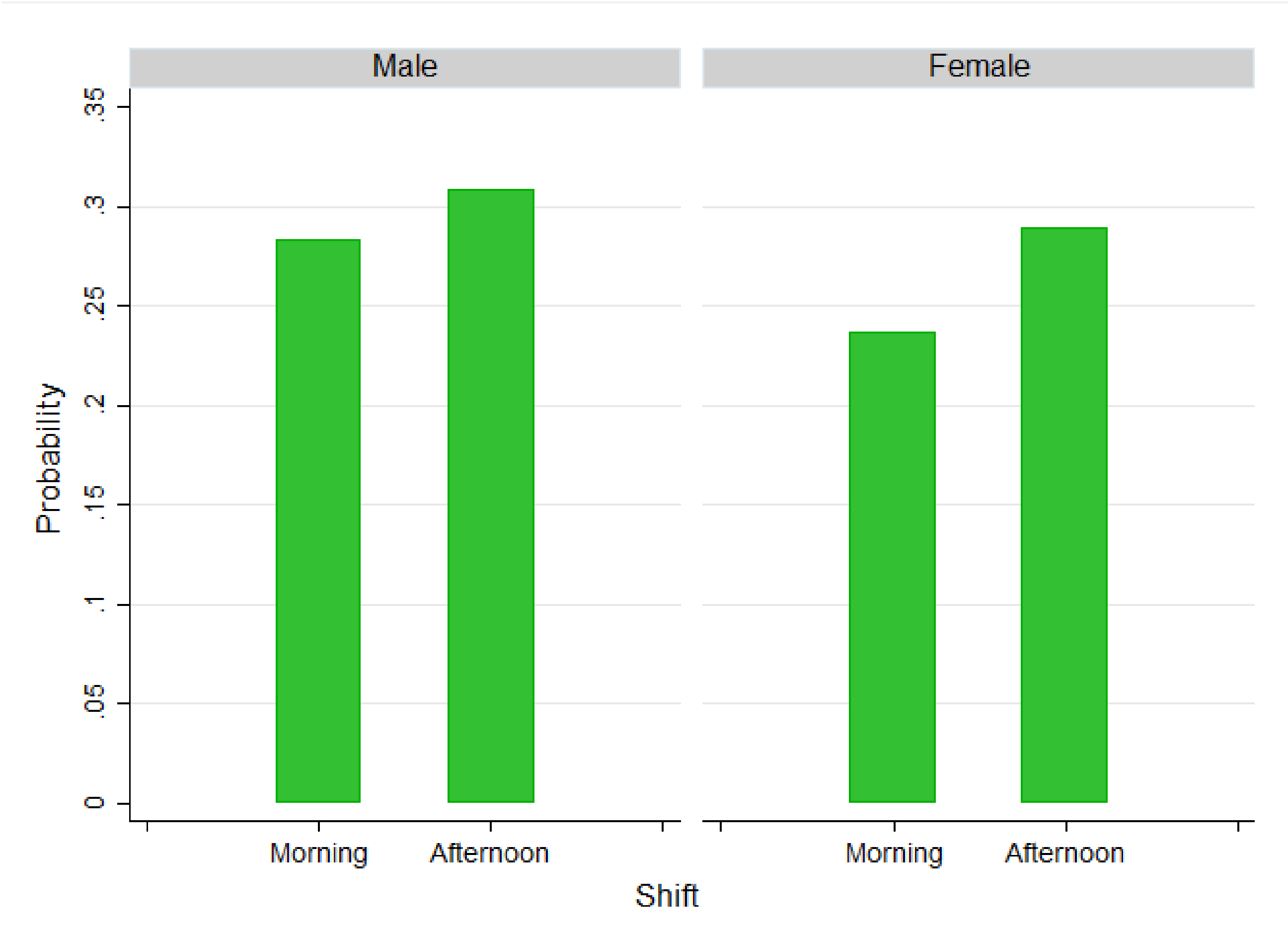
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted line is predicted from a local linear regression with a bandwidth of 0.4.

Figure 9: Discontinuity in the desetion probability by group



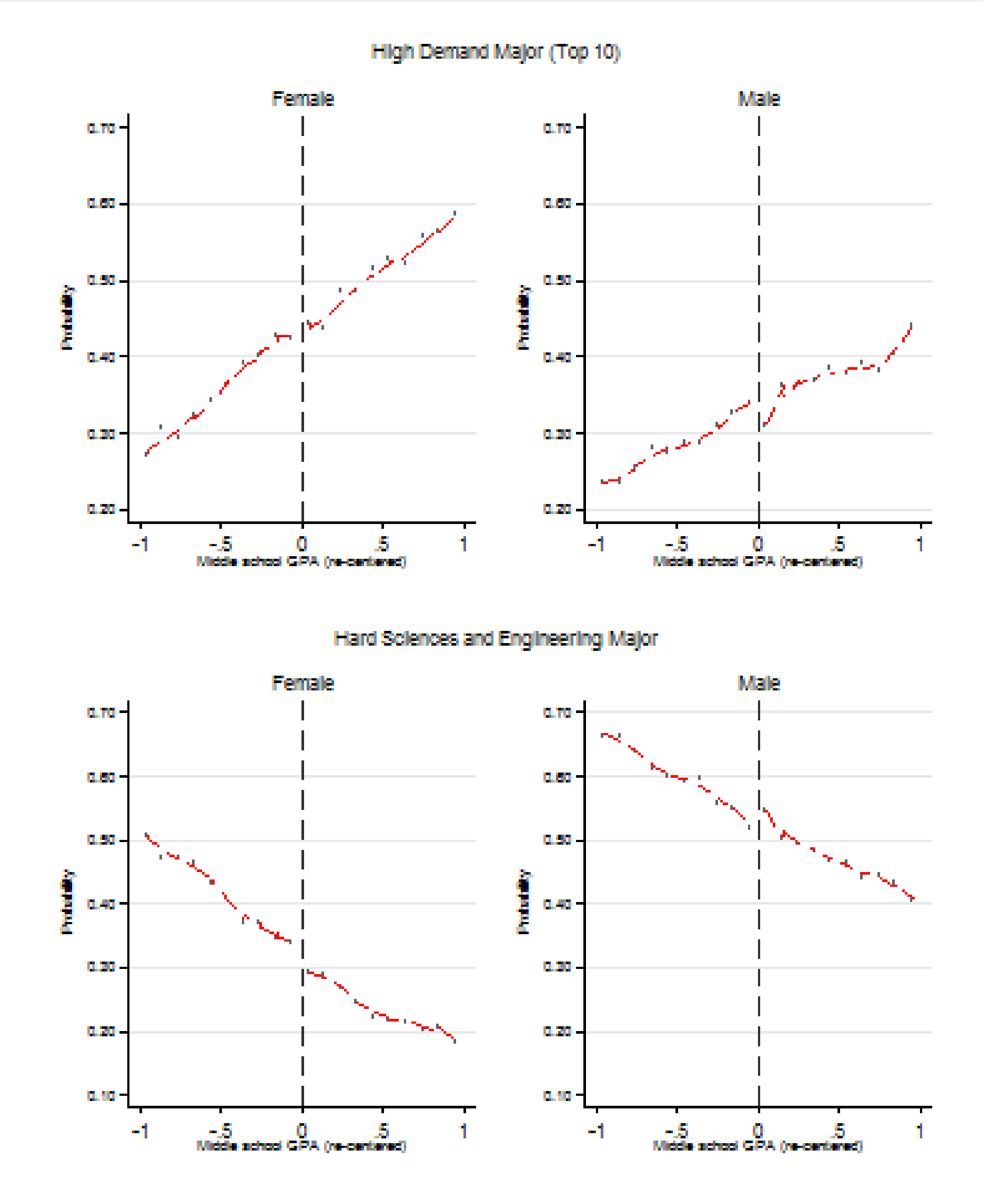
Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted lines are predicted from local linear regressions with a bandwidth of 0.4.

Figure 10: Drop-out probability by ranking



Notes: The bars represent the dropout probability for a student with average characteristics, fixing her position to tha last (0=worst) and first place (1=better), for the moorning and afternoon shift respectively, and her re-centered middle school GPA fixed in at the threshold (=0) for boh cases.

Figure 11: Discontinuity in the probability of admission to UNAM



Notes: Each circle is the mean of the outcome in an interval of 0.1 around the central point. The dotted lines are predicted from local linear regressions with a bandwidth of 0.4.