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Closing the Gap

Effect of a Gender Quota on Women's Access to Education in Afghanistan

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Abstract

Affirmative action is a promising solution to the crucial challenge of bridging the gap in women's access to higher education in low- and middle-income countries (LMICs). This paper uses public universities' matriculation data from 2013–2018 and difference-in-differences estimators to examine the causal impact of a gender quota on women's educational opportunities in Afghanistan. The quota increased the proportion of women in the treated concentration group by nine percentage points and the share of women from low socio-economic status by three percentage points. The expansion was associated with a 0.04-unit decline in the average score ratio of female-to-male applicants, driven by a reduction in the score threshold needed for women's admission. The effects were condensed in competitive concentrations, where the overall share of women and women with low SES increased by 17 and four percentage points, respectively. The findings suggest that affirmative action is a viable option for addressing the gender gap in fragile settings..

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Closing the gap: Effect of a gender quota on women's access to education in Afghanistan

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Abbreviations

GPI: gender parity index

IHEs: institutions of higher education

LMICs: low- and middle-income countries

MoE: Ministry of Education

MoHE: Ministry of Higher Education

NEXA: National Examination Authority of Afghanistan

PMB: private marginal benefits

SDGs: sustainable development goals

SES: socioeconomic status

VIIRS: visible infrared imaging radiometer suite

1 Introduction

In low- and middle-income countries (LMICs), primarily in fragile and conflict-affected settings, achieving gender-equal access to institutions of higher education (IHEs) remains a priority. Such access is pivotal for meeting the United Nations Sustainable Development Goals (SDGs)—particularly SDG4, focusing on inclusive, quality education, and SDG5, advocating for gender equality—and amplifying socioeconomic benefits (Chaaban & Cunningham, 2011; Hill & King, 1995; Psacharopoulos & Patrinos, 2018). While the significance of post-secondary education is growing globally, LMICs struggle with lower enrollment level and a higher gender gap. Despite the vast expansion of IHEs in these regions, ensuring women's access remains a substantial barrier. This obstacle impedes the reduction of gender inequality in IHEs (Ilie & Rose, 2016) and hampers women's long-term labor market participation. In Afghanistan, fragility and cultural barriers have limited women's access to post-secondary education (Baiza, 2013; Darwish & Wotipka, 2022; Hayward & Babury, 2015; Hayward & Karim, 2019; Shayan, 2015). Since the early 2000s, educational opportunities have expanded significantly, notably for girls in Afghan public institutions (Najam & Johnston, 2023). However, the gender parity index (GPI) of public post-secondary education remains one of the lowest globally. Following the Taliban's ban on women's education (since 2021), the GPI is expected to decline further.

To combat educational inequalities, policymakers and educational institutions have adopted interventions such as affirmative action to enhance the presence of underrepresented groups in IHEs. These policies are typically target-based, offering preferential treatment to specific applicant subgroups who face structural barriers to accessing education. Several types of affirmation action have been implemented: gender quotas (Bagde et al., 2016); racial-quotas, predominantly in the United States (Arcidiacono et al., 2015; Card & Krueger, 2005; Hinrichs, 2014; Long, 2004; Rose, 2005) and Brazil (Estevan et al., 2019; Francis-Tan & Tannuri-Pianto, 2015; Mello, 2022; Vieira & Arends-Kuenning, 2019); caste- and/or class-based quotas, primarily in India (Basant & Sen, 2020; Bertrand et al., 2010; Cassan, 2019) and Israel (Alon & Malamud, 2014); and geographic quotas, in Sri Lanka (de Silva et al., 2021). Most of the literature indicates that affirmative action is instrumental in increasing access to education in historically underrepresented populations.

Public universities in Afghanistan operate under a stringent centralized system. Admission to a public university is determined solely by the applicants' scores on the annual nationwide entrance exam for public universities, known as the *Kankor* examination. Female applicants tended to score lower than their male counterparts in the Kankor. This disparity in performance is attributable to the systematic underinvestment and cultural barriers Afghan women face in accessing post-secondary education (Bamik, 2018; Hayward & Babury, 2015; Najam & Johnston, 2023), which is exacerbated by conflict (Darwish & Wotipka, 2022). In 2016, the Afghan government introduced a gender quota for admissions to address gender disparities and promote women's long-term labor participation. The policy expanded until the Taliban's return. This policy allocated seats at the enrollment unit level (*concentrations*) by gender in particular universities and courses of study. These concentrations served as the *treated units*. Consequently, the admissions competition was gender-specific—female applicants competed with other females, and male applicants competed with other males—for gender-designated seats in treated concentrations. Conversely, the other concentrations maintained open competition[1] (hereafter, *untreated units*).

In this paper, I examine the short-term efficacy of gender quotas on women's matriculation[2], especially those from low socioeconomic status—proxied by districts' average nightlight data—in Afghan public universities. Specifically, I explore variations across study units and over time to assess the causal impact of gender quotas on the share of matriculated female students and score-related outcomes using the difference-in-differences (DD) methods. The causality of the DD estimates relies on the central parallel

[1] Admission is solely based on applicants' Kankor score.

[2] Kankor participants receive a single admission offer from the administering authority. The terms 'matriculation,' 'admission,' and 'enrollment' are used interchangeably.

trend assumption. This implies that in the absence of the quota intervention when accounting for the fixed effects, the outcome trends for the treated and untreated groups would follow a similar pattern as the trends between the two groups in the pre-treatment period. I found evidence from an event study analysis that the parallel trends assumption holds.

I use the universe of matriculation results of Kankor test-takers from the academic years 2013–2018. This dataset contains detailed applicant characteristics for 1.51 million participants, such as gender, test score, high school name, and the unit of study to which they were admitted. For this study, I focus *exclusively* on a subset of 336,221 applicants admitted to public universities over six-years. I employ district-level monthly average luminosity data from 2014–2015 to indicate economic development[3] and identify applicants from areas of low socioeconomic status (SES). This categorization enables me to assess the impact of the quota intervention on the participation and score-related outcomes of female applicants with high and low [4] statuses.

The quota led to a nine-percentage point increase in the matriculation rate of female applicants in the treated concentrations, a 32% increase over the control group mean. Specifically, the quota raised the matriculation rate of female applicants from low-SES districts by three percentage points, a 30% increase compared to the control group mean. This expansion in women's admissions to public IHEs has lessened the gender gap. However, it has also resulted in a reduced score threshold for female students' admissions to treated units. This is revealed by a significant decrease of 0.04 units in the average score ratio of female-to-male applicants in the treated concentrations, a 4% reduction compared to the control group mean. This indicates that the preferential treatment enrolled female students with lower Kankor scores. This favored treatment might raise concerns about applicants' academic performance post-admission,

[3] I acknowledge the coarse nature of this classification. However, given the lack of granular metrics at the applicant and/or district-level in Afghanistan, the use of nightlight data provides a plausible indicator of economic development at the district-level. I am unable to differentiate between the socioeconomic statuses of individual applicants level and instead rely on district classifications.

[4] I use the average of luminosity across district as the source of operationalization. Low-socioeconomic status indicates districts with an average luminosity value less than the mean.

which is commonly referred to as a mismatch between applicants' preparation and the fields of study (Frisancho & Krishna, 2016; Rose, 2005).

Additionally, I assess the effects of the gender quota on women's access and score-related outcomes based on the competitiveness of academic programs. Highly competitive academic programs encompass concentrations within computer science, economics, engineering, law and political science, and medical studies, collectively referred to as CEELM programs[5], across public universities. Before 2016, female students constituted an average of 17% in CEELM programs, marking an 11% deficit compared with their representation in non-CEELM programs. I found that the quota led to a 17-percentage point rise in the share of female applicants and a four-percentage point increase in the share of low-SES female applicants in highly competitive concentrations. This nearly doubled the share of female students compared to the control group mean, suggesting a significant reduction in gender disparities in the selected concentrations. This is a crucial step towards enhancing women's participation in the workforce in much-needed areas.

This study offers a pivotal contribution to empirical research assessing the effects of affirmative action on marginalized groups' access to educational opportunities and the associated implications of quality-access trade-offs. First, to my knowledge, this is one of the first studies to examine the impact of affirmative action on women's access to higher education in fragile and conflict-affected settings. Existing studies in this domain have primarily focused on more stable environments, such as the US, India, and Brazil. Second, this study contributes to the literature that investigates the causal effects of affirmative action (Basant & Sen, 2020; Bertrand et al., 2010; de Silva et al., 2021; Frisancho & Krishna, 2016; Mello, 2022), and/or a ban of affirmative action (Antonovics & Backes, 2014; Arcidiacono et al., 2015; Card & Krueger, 2005; Epple et al., 2008; Hinrichs, 2014; Long, 2004). The focus has been on marginalized groups' access to educational opportunities, emphasizing varying impacts across different socioeconomic strata (Backes, 2012; Estevan et al., 2019; Francis & Tannuri-Pianto, 2012; Francis-Tan & Tannuri-Pianto,

[5] Among the CEELM programs, no concentrations in economics and the law and political science are treated.

2015), and the selective field of studies/colleges (Alon & Malamud, 2014; Bagde et al., 2016; Hinrichs, 2012; Howell, 2010; Vieira & Arends-Kuenning, 2019). Third, I assess the efficacy of an intervention targeting an increase in the potential supply of qualified women for the labor force. The lack of qualified female applicants—nationally and within refined sectors—presents a significant challenge to achieving employment quotas (Howard & Prakash, 2012; Myers, 2007; Peck, 2017; Prakash, 2020). Finally, this study examines a gender quota within Afghanistan's unique centralized admission system, where applicants select their study fields without knowing their Kankor exam scores, highlighting the significant role of affirmative action in expanding the availability of educational opportunities at the national level for female applicants.

2 Literature review

Affirmative action comprises target-based policies and practices. The primary objective is to enhance opportunities for specific applicant sub-groups facing systemic barriers to education and employment. This includes preferential consideration of historically underrepresented sub- groups based on factors such as gender, caste, class, region, and race, among others. An extensive body of literature—predominantly from India, the US, and Brazil—examines the direct and indirect impacts of adopting and eliminating affirmative action on (post-)matriculation outcomes.

Regarding the efficacy of affirmative action in college admissions, the findings are consistent across various contexts. In India, the caste-based system creates social stratification, leading to structural inequalities in the education and employment of minorities (Bertrand et al., 2010; Howard & Prakash, 2012). Nevertheless, affirmative action mitigates the widening inequality. Bagde et al. (2016), Basant & Sen (2020),Bertrand et al. (2010), Lee (2021) and Cassan (2019) find that caste-based quota policies increase the representation of disadvantaged castes in post-secondary education. In Brazil, Estevan et al.

(2019), Francis & Tannuri-Pianto (2012), Francis-Tan & Tannuri-Pianto (2015), Mello (2022), and Vieira & Arends-Kuenning (2019) indicate that racial and group-specific policies boost the enrollment of the targeted population. In Israel, Alon & Malamud (2014) reveals that affirmative action policies enhance the probability of admission and enrollment, particularly in selective majors. Similarly, in Sri Lanka, de Silva et al. (2021) find that geographically-targeted policies improve the representation of students from disadvantaged regions.

In the US, affirmative action in higher education involves race-based admission selections—a divisive subject (Arcidiacono et al., 2015). Several universities and states have chosen to ban affirmative action due to controversies[6] and rulings from the US Supreme Court regarding race-based considerations in college admissions (Baker, 2019). Card & Krueger (2005) indicate that the ban on affirmative action reduced the overall admission rate for African-American and Hispanic students. However, highly qualified minority applicants continue to send their test scores to selective state institutions. Hinrichs (2012) shows that an affirmative action ban results in decreased enrollment of underrepresented minorities at selective colleges, although there is no effect at typical colleges. Similarly, Backes (2012) reports a decline in minority student enrollment. Hinrichs (2014) asserts that banning affirmative action decreases the number of minority graduates. Nevertheless, the graduation rate for minorities has increased because of the shifting composition of minority students in selective colleges. Furthermore, Epple et al. (2008) and Howell (2010) emphasize that an affirmative action ban can significantly reduce minority representation in top-tier institutions. Klasik & Cortes (2022), Long (2004; 2015), and Antonovics & Backes (2014) reveal that alternative policies fall short of achieving minority representation levels comparable to those achieved under affirmative action.

One subset of the literature assesses the effects of affirmative action's policies on human capital

[6]For a detailed discussion about the trade-offs imposed by affirmative action and an extensive review of the literature, see (Arcidiacono & Lovenheim, 2016), (Fryer & Loury, 2005), and (Holzer & Neumark, 2000).

development. In India, Khanna (2020) and Cassan (2019) demonstrate that affirmative action improves years of schooling and educational attainment, respectively. In the US, Akhtari et al. (ming) find that affirmative action reduces the racial gap and encourages pre-college human capital investment.

Mixed evidence exists on the impacts of affirmative action on minorities' academic performance. Rose (2005) and Frisancho & Krishna (2016) find that students benefiting from affirmative action lag behind their peers academically, particularly in selective majors. Conversely, Alon & Malamud (2014) suggest that students admitted based on preferential treatment do not fall behind academically, regardless of their selection of majors.

The primary focus of affirmative action policies in education is to address educational disparities. However, they also play a pivotal role in shaping the employment outcomes of minorities. Howard & Prakash (2012) posits that the impact of the employment quota is linked to the schooling years of minorities, highlighting the interlinkages between educational progression and economic mobility. Myers (2007) finds that abolishing employment-based affirmative action is correlated with a decline in minority labor force participation, further illustrating the broader ramification of these policies. Thus, policies to rectify educational disparities could also serve as a mechanism to alleviate employment inequalities. This is exemplified by the gender quota in public IHEs introduced by the Afghan government, which sought to expand the supply of qualified women in the labor force.

3 Background

3.1 Admission to Afghan public universities

The admission to public IHEs is strictly based on applicants' Kankor scores. Kankor is a nationwide entrance exam[7], held annually countrywide for applicants, predominantly new high school graduates interested in pursuing undergraduate studies at public universities. This is the only mechanism through which applicants can attain admission into public universities' daytime undergraduate programs, as shown in Figure A1.1. The examination has been administered by the National Examination Authority of Afghanistan (NEXA) since 2018 and was previously overseen by the General Directorate of Examinations within the Ministry of Higher Education (MoHE). The administering authority is also responsible for grading all test-takers and finalizing the Kankor results before the start of each academic year. Applicants receive only one admission offer from the administrating authority, and it is almost impossible to transfer from one admitted concentration to another within and/or across public IHEs.

The Kankor exam comprises 160 multiple-choice questions derived from all subjects[8] taught in Afghan public high schools in grades 10–12[9]. The Kankor score range is 0–360 points; on average, each question is worth 2.25 points. From 2013–2018, the exam was held nationwide over several weeks, and the administering agency finalized admission decisions after all the exams were completed. The questions are drawn from a large question bank; thus, the questions vary across and within exam regions[10], although the pro-

[7] An open competition among all participants; it serves as a filtering mechanism to admit qualified students—based on their performance on the exam, measured by their score—into public universities.

[8] The subjects taught in grades 10–12 in public schools are uniform across the country. They are developed by the central curriculum directorate at the Ministry of Education (MoE) in Kabul, Afghanistan, ensuring no variability in the topics covered across regions. However, there are disparities in school and teacher quality. Students in public schools do not have the option to enroll in specific subjects or tracks of study; instead, they must undertake all the courses offered for each grade.

[9] While students in private schools receive instruction in additional coursework/topics, these schools are required to offer the fundamental subjects for each grade as designated by the MoE.

[10] There is a slight chance that some questions from an exam taken earlier in region K will appear in a later exam taken in region L.

portion of questions from each subject topic remains the same, regardless of the exam location and date. The exam lasts two hours and 40 minutes[11], after which test-takers receive a selection sheet from the proctors[12]. The selection sheet contains a list of concentrations and their enrollment capacity, grouped by major or university department. After the first adoption of the gender quota in 2016, the treated concentrations' enrollment capacity was separated by gender with a unique concentration gender-specific code, as seen in Figure A1.2.

At the end of the Kankor exam, applicants select and rank up to five concentrations despite not knowing their Kankor scores. The applicants enter the unique code for each concentration into the answer sheet. The administering authority uses this to finalize the matriculation decisions. The exam is open to all. Irrespective of the concentration type (e.g., medical or literature), applicants must achieve a qualifying score to ensure admission to their chosen concentrations. There is no fixed score threshold, as it can vary annually depending on the number of applicants for a particular concentration. After the nationwide Kankor examinations are concluded, the administering authority begins grading and finalizing admission decisions. They enroll high-scoring students in concentrations based on their scores until all available spots are filled. The gender quota adjusted the enrollment criteria by changing the focus from scores in treated concentrations to considering both scores and sex.

Table 1 shows the descriptive statistics of annual high school graduates, Kankor exam participants, and the matriculation rate in Afghanistan for 2013–2018. On average, 220,000 students graduated from high school, among which 36% were girls, as shown in Panel A. On average, approximately 190,000 applicants participated in the Kankor exam in the between the 2013–2018 academic years (Panel B), of whom 33% were women. Female applicants were less likely to participate in the Kankor exam as a share of girls who graduated from high school, as shown in Column 4 of Panel B. Additionally, regarding

[11] The NEXA authority has recently extended the exam duration to over 3 hours.

[12] Public university lecturers/professors serve as the official proctors. The administering authority rotates proctors across regions to oversee the exam, although most are local lecturers and/or professors.

matriculation into public and private IHEs, the GPI was 1:3 and 1:4, respectively. The share of women admitted was considerably worse than the share of female high school graduates, as seen in Column 4 of Panels C and D. Finally, female applicants were significantly more likely to score lower than male test-takers among all applicants, as seen in Panel E, and among matriculated students, as seen in Panel F of Table 1.

Table 1: Descriptive statistics for Kankor exam participants between 2013-2018

	Mean (1)	Standard Dev. (2)	% female / female to male avg. score ratio (3)	As a share of high school graduates (Panel A) (4)
Panel A: High school graduates in *thousands*				
Female	78.53	(9.77)		
Male	141.19	(15.13)		
Total	219.72	(24.49)	36%	
Panel B: Kankor test-takers/Applicants in *thousands*				
Female	62.24	(10.31)		79%
Male	127.78	(19.22)		90%
Total	190.02	(28.83)	33%	86%
Panel C: Newly admitted in public IHEs in *thousands*				
Female	14.64	(3.03)		19%
Male	41.39	(1.35)		29%
Total	56.04	(3.37)	26%	25%
Panel D: Newly admitted in private IHEs in *thousands*				
Female	9.23	(1.83)		12%
Male	35.99	(5.65)		25%
Total	45.22	(7.47)	20%	20%
Panel E: Average score for Kankor applicants (0-360)				
Female	186.81	(44.66)		
Male	193.23	(48.43)		
Total	189.41	(50.44)	0.97	
Panel F: Average score for admitted students in public IHE (0-360)				
Female	235.66	(47.04)		
Male	236.47	(46.05)		
Total	236.26	(46.31)	0.99	

Note: the raw data is compiled from multiple sources, mainly Afghanistan yearly statistics books published by the National Statistics and Information Authority (NSIA), Ministry of Education (MoE), and the Kankor results for 2013–2018.

3.2 Gender quota

The gender quota for admission to public universities was first introduced in the 2016 academic year and gradually expanded until the Taliban returned to power in 2021. Female test-takers typically scored significantly lower than male participants, both among all Kankor participants and among those admitted to public IHEs, as shown in Panels E and F of Table 1. Najam & Johnston (2023) show that the proportion of female student enrollees in public IHEs has risen over time. Despite the increase in women's access to higher education, public universities' strict score-based admission criteria exacerbate gender inequality, especially in highly selective programs. This disparity in performance might stem from the systematic underinvestment and cultural barriers Afghan women face in accessing post-secondary education (Bamik, 2018; Hayward & Babury, 2015; Najam & Johnston, 2023), which is exacerbated by conflict (Darwish & Wotipka, 2022).

The MoHE has prioritized improving women's access to higher education, as outlined in the Higher Education Strategic Plan II 2010–2014 (Ministry of Higher Education, 2009) and the HE Strategic Plan III 2016–2020 (Ministry of Higher Education, 2015). The introduction of a gender quota in 2016 aimed to reduce gender disparities in higher education and boost women's participation in the country's workforce, particularly in leadership roles in public offices. Yari & Schafer (2021) show that in 2018, Afghan women constituted approximately 22% of the Afghan civil service and held only 7.5% of the decision-making roles. Gender quotas are a crucial step in developing the human capital of the targeted group—in this case, enhancing the supply of qualified, educated women. The gender quota allocated, on average, 37% of seats for female test-takers in the treated concentrations at 12 out of 37 public universities[13]. Treated concentrations were selected based on the country's need for professionals in specific fields of study, such as medicine, computer science, and public administration. Another consideration was whether female test-takers were less likely to secure admission in fields such as engineering, computer science, law, and political science due to intense competition in a score-based admission approach. Additionally, as shown in Table A3.1, the treated concentrations were primarily located at regional universities. Thus, the policy expanded educational opportunities for women in highly competitive and/or respected public

[13]See Table A3.1 for the share of ever-treated concentrations in a given university.

IHEs nationwide.

In 2016, the policy was implemented for Kankor exam test-takers applying for their freshman year in that academic year. The MoHE introduced a biometric system for applicant registration and verification[14] in the same year to address allegations of fraud and corruption against the Kankor exam in previous years. The MoHE publicly announced the biometric registration system, but not gender-specific changes, in the enrollment approach of treated concentrations in the first-year of implementation[15]. Therefore, the level of awareness among applicants regarding the changes in the enrollment method—from open competition to gender-specific considerations—remained ambiguous. The absence of a public announcement suggests that this information was not evenly distributed across applicants and regions, at least during the first year of adoption. This lack of advertisement has profound implications on students' academic decisions. First, a lack of complete information beforehand might have led to misaligned expectations regarding the chances of acceptance. Second, students might have been excluded from the concentrations for which there was a higher likelihood of acceptance due to the gender quota allocation. Finally, students from privileged backgrounds might have accessed this information through informal channels, while other applicants remained uninformed, raising equity concerns.

Additionally, I report the t-balance test for the primary outcomes before the introduction of the gender quota in Table B3.1. The results show that the overall share of female applicants and the share of female applicants from low-SES groups who matriculated in treated concentrations were significantly lower than the control group mean. The quota policy, which serves as a quantity intervention, aims to improve the rate of female students by distributing seats to gender-specific proportions in treated concentrations. On average, this rate was greater than the actual share of female students in the period

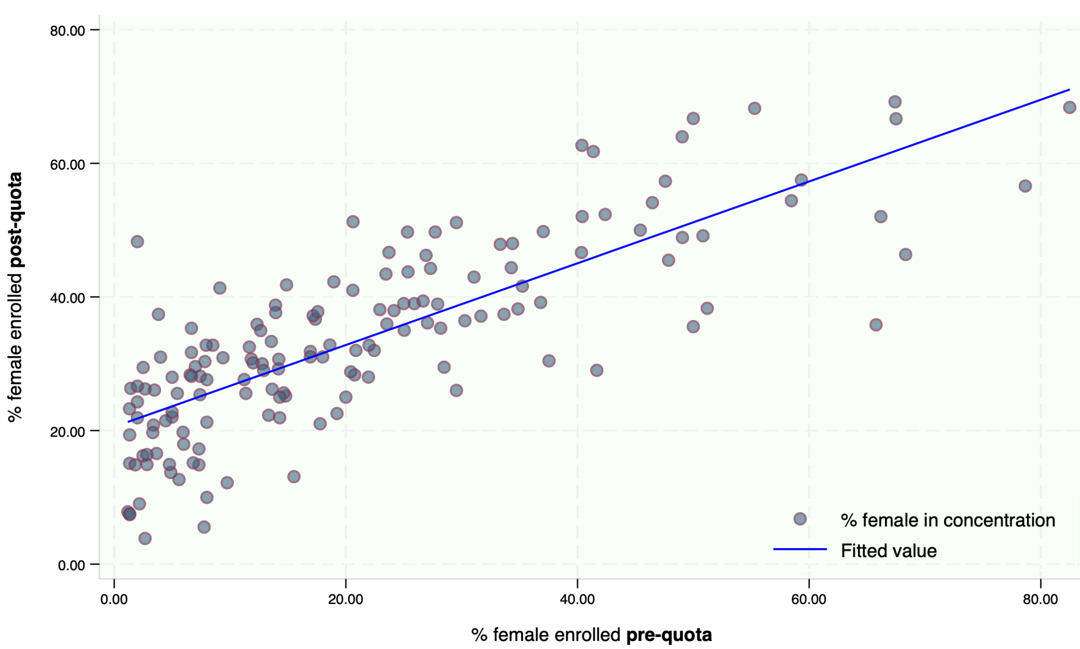
[14]This universal change does not threaten the identification strategy as it affects all applicants equally. However, the introduction of the biometric system might discourage certain groups from participating in the Kankor exam.

[15]I verify that concentrations received official communication from the MoHE about the gender quota implementation. However, I found no evidence indicating that this decision was communicated to test-takers across the country, at least before the Kankor exam for the 2016 academic year.

before the quota's implementation. Thus, I assess whether the policy expands educational opportunities for female applicants and whether such an expansion is associated with lowering the score threshold required for the admission of female students in treated concentrations.

Figure 1 depicts the relationship between the average share of female students in the post-quota (y-axis) and pre-quota (x-axis) periods for the treated concentrations. This figure underscores the significant increase in the proportion of female students during the post-quota period, especially in concentrations where the female student share was previously below 20%. Furthermore, the figure highlights that, owing to the gender quota's allocation of seats, the share of female students decreased in some treated concentrations during the post-quota period.

Figure 1: Share of female students in treated units in the pre- and post-quota periods



Source: Kankor dataset 2013-2018.

The policy was implemented in a staggered manner. However, most concentrations (≈ 85% of treated units) were treated in 2016. Its reach expanded gradually after 2016. Notably, some of this expansion was driven by the disaggregation of enrollment in certain concentrations into multiple units (for further details, see Appendix A.4) and by the expansion of academic programs[16]. Academic programs refer to the number of concentrations across universities that offer a particular academic degree[17], such as economics, engineering, and other programs. I account for these changes in the empirical specifications by including various fixed effects. Finally, in principle, there may be discrepancies between matriculated applicants and those eventually attending public IHEs. Nevertheless, the gap is likely negligible considering the institutional features (e.g., limited transfer possibility, free tuition, and dormitories) and future return on education. It should not pose a significant threat to the consistency of the findings.

4 Data

I compiled three datasets to assess the gender quota impact on outcomes of interest. First, I attained the Kankor matriculation dataset for 2013–2018, from publicly available sources to compute variables of interest. Second, I obtained district-level nightlights data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Stray Light Corrected Nighttime Day/Night Band Composites Version 1 via Google Earth at the second administrative unit level. Finally, I used the school database in Afghanistan available on the Ministry of Education (MoE) website. It contains information on school names and district locations, allowing me to match test-takers to their school districts.

First, in the Kankor dataset, I observed applicants' gender, final test scores, high school name, high school graduation year, the province where the applicants took the exam, the institution's name for those who matriculated into 2-year associate degrees, and university-unique-concentration identifier for applicants enrolled into 4-year public IHEs on 1,151,042 Kankor test-takers for 2013–2018. I limited the data to those applicants enrolled into the 4-year public universities (29% of all test-takers). The

[16]See Table A2.1 for the conceptual difference between concentrations, academic programs, and universities.
[17]See Table A3.2 for the share of ever-treated concentrations across academic programs.

treatment status for a concentration was jointly identified using two primary sources: [1] the Kankor exam selection sheet produced by the administering authority as an example, is shown in Figure A1.2, and [2] the Kankor matriculation dataset, which explicitly denoted whether an applicant was admitted into the treated units. If there were any discrepancies between the two sources, the author contacted a specific university and the MoHE to identify the treatment status for these concentrations. For example, four religious' studies units were admitting applicants based on gender before 2016 in the matriculation dataset. Nonetheless, these units historically enrolled students in a gender-specific manner for cultural reasons, and were not subject to the gender quota. Hence, these concentrations were not considered treated units because of the gender quota policy in the analytical sample.

The yearly descriptive statistics of Kankor participants—the share of female students and that of female students admitted into 4-year public IHEs are reported in Table B1.1. The number of concentrations increase over time, as shown in Table B1.1, which does not threaten the identification strategy, as I controlled for the concentration fixed effects. This increase was driven by the splitting of enrollment levels from general admission into several concentrations in some fields of study, the enlargement of academic programs, and the establishment of universities for further details (see Appendix A.4).

Moreover, I obtained monthly nightlight data as an average of the Day/Night Band radiance values in nanoWatts/cm2/sr units from Stray Light Corrected VIIRS composited at the district level for 2014–2015[18]. I excluded pixels with zero values across all images to increase the accuracy of the zonal statistics computations at district level. The use of nightlight as a proxy for economic development and measure of economic activities (Basihos, 2016; Beyer et al., 2018; Galdo et al., 2020; McCord & Rodriguez-Heredia, 2022; Sänger et al., 2022) is becoming popular. High economic development, which correlates with enhanced service provision, will enable women to access better educational services. Conversely, a low level

[18]The Visible Infrared Imaging Radiometer Suite (VIIRS) Stray Light Corrected Nighttime Day/Night Band Composites Version 1 data were not available prior to 2014.

of nightlight is indicative of dire economic situations and disruptions in public services (Sänger et al., 2022). Nightlight provides a rough indicator. However, given the lack of granular metrics at the applicant and/or district levels in Afghanistan, nightlight data provides a plausible indicator of economic development at the district level. Therefore, I cannot differentiate between applicants' socioeconomic statuses at the individual level and instead rely on district classifications. I used the two-year pre-treatment average luminosity by district as a binary indicator to identify low-SES applicants, operationalized as districts with luminosity lower than the mean (0.2678 nanoWatts/cm2/sr) in the pre-treatment period. I used this indicator to examine the impact of quotas on the share of female students from low SES. To achieve this objective, I successfully matched 95.4%[19] of all matriculated applicants (336,151) to their districts of origin. I accomplished this by merging student records at the district level based on school and province names (i.e., the province from which they participated in the Kankor exam) with the applicant's high school districts using the comprehensive school database from the MoE.

5 Empirical Strategy

The gender quota implementation started in 2016 and expanded in the following years. The quota distributed the available seats at some concentrations based on gender but maintained open competition at other concentrations. Thus, I exploited the variation across concentrations and over time to study the causal impact of the gender quota on the share of matriculated female students and score-related outcomes in treated units using the following DD model shown in Equation 1:

$$Y_{isut} = \alpha + \beta Treat_{isut} + \lambda_{isu} + \rho_{st} + \gamma_{ut} + \theta_t + \epsilon_{isut} \tag{1}$$

[19]The reasons for the 4.6% of unmatched applicants include multiple schools located in different districts within the same province. However, labels for these schools are entered identically without any unique district information, making it difficult to identify the exact school from which an applicant graduated in the matriculation dataset. Additionally, applicant school names are missing, either because they were not entered, or the applicants completed their high school studies in neighboring countries (e.g., Pakistan and Iran).

The Y_{isut} are the outcomes of interest for a concentration i at university s, academic program u, and time t. β is the estimate of interest or the quota policy effects, and λ is the fixed effect for the concentration i at university s and academic program u; ρ is the fixed effect for university s in time t, γ is the fixed effect of academic programs u in time t, where θ is the year fixed effect[20], and ϵ_{isut} is the error term, and models are estimated with the cluster standard error at the concentration level.

Concentrations, academic programs, and institutional-level selectivity are critical aspects that must be considered when studying matriculation in post-secondary education at the national level using a centralized matriculation system. This issue is more prominent in developing nations, where applicants are more likely to choose prestigious fields of study, causing the admission process for specific concentrations to become more competitive than others, λ_{isu}, (the concentration-university-academic program fixed effect) controls for systematic differences across concentrations.

The university-by-year fixed effect ρ_{st} captures any factor affecting an entire university in a particular year, such as changes in security conditions in the area where the university is located or university-level infrastructure development (e.g., the expansion of girls' dormitories). For instance, the gradual withdrawal of the International Security Assistance Force from across the country to pre-designated locations under the Resolute Support Mission by the end of 2014, led to deteriorating security conditions in regions where security transitions occurred (Fetzer et al., 2021). Consequently, some universities become less favorable to applicants due to such regional shocks, which are likely to change the composition of applicants choosing a given university in year t. Additionally, university-level infrastructures development (e.g., buildings and dormitories) is another factor that is likely to change the composition of students selecting a given university. The ρ_{st} captures any regional shocks, the effects of which vary over time and across universities.

The academic program by year fixed effect γ_{ut} controls for any unobservable factor affecting an

[20]This can be dropped in the model as I control for university-year and academic program-year fixed effects.

academic program over time and is not university-specific. There are 17 academic programs across the 37 public universities, as shown in Table A3.2. For instance, if there is an expansion of a particular academic program (e.g., engineering or medicine) in time t, such expansion increases the availability of choices for applicants. Thus, an applicant who is determined to study a specific concentration (e.g., civil engineering, econometrics) will likely utilize the expansion and select their preferred concentration in newly established academic programs across universities. This factor changes the composition of applicants enrolled in specific academic programs over time and is controlled by γ_{ut}.

The inclusion of these fixed effects is important for the DD estimator to differentiate trends and account for common shocks to attain a credible estimate of the quota policy's impact on the outcomes of interest. The identification strategy provides a causal effect as long as the central assumption of parallel trends between the treated and untreated units in the absence of the policy (Angrist & Pischke, 2009; Cunningham, 2021; Huntington-Klein, 2022; Morgan & Winship, 2014), conditional on fixed effects, is not violated. If this assumption holds, we expect that the outcome trends between the treated and comparison groups, conditional on fixed effects, would follow a similar pattern to that between the two groups in the pre-treatment period. To check for parallel pre-treatment trends, I ran the following event study model:

$$Y_{isut} = \alpha + \sum_{j=-3}^{2} \beta_j Treat_{isut,t-j} + \lambda_{isu} + \rho_{st} + \gamma_{ut} + \theta_t + \epsilon_{isut} \tag{2}$$

In Equation 2, the baseline year is the year before to the policy adoption in concentration isu, I allowed for dynamic leads and lags, and the remaining terms are described in Equation 1. I find plausible evidence from the event study analysis reported in Appendix B.4, that the trends between the treated and controls units, conditional on fixed effects, are not statistically different in the pre-treatment period. The policy was implemented without advance announcements before its enactment in 2016, limiting any anticipation effect.

Another concern was the staggered implementation of quota adoption in some concentrations in the post-2016 period, as discussed in recent literature (Borusyak et al., 2022; Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021), which suggest the conventional two-way fixed effect may fail to provide unbiased estimates. In this study setting, differential treatment timing does not pose a significant threat to the estimates because most concentrations adopted a quota policy in 2016, with a few late adopters, which were mostly newly established concentrations with no variation in the treatment status and absorbed by the concentration-university-academic program fixed effect. Additionally, once a concentration fixes the allocated slots by gender, it remains treated, and the allocation level does not change, reducing the risk posed to the TWFE estimate stated in recent literature. Nevertheless, I report the findings and event study results using the estimators of Borusyak et al. (2022) and Sun & Abraham (2021).

6 Results

6.1 Main results

Table 2 reports the overall impact of gender quotas on women's access to educational opportunities and score-related outcomes. The quota increased the share of female students at the treated concentrations by nine percentage points, a 32% increase relative to the comparison group mean, as seen in Column 1. Specifically, the quota improved the share of female students from low-SES backgrounds by 3 percentage points, a 30% increase compared to the control group mean, as shown in Column 2. These findings highlight the effectiveness of the quota in closing the gender gap in higher education by amplifying women's educational opportunities.

Nonetheless, as seen in Columns 3–8, score-related outcomes indicate that such an expansion is associated with a reduction in the score threshold required for women's admissions in treated concentrations. As result of the quota, I found that the average score of matriculated female students in treated units declined by 11 points, a 5% decrease relative to the comparison group mean. This decrease was driven by a substantial decline of 14 points in the average score of female applicants from the high-SES group, representing a 6% decrease compared to the control group mean. The average score of female students admitted from low SES decreased by 5 points or 2% (Column 6 in Table 2).

There were no significant changes in the average scores of the admitted male applicants in the treated concentrations. This result is unexpected because, owing to the allocation of seats at these concentrations[21], the competition among male applicants should have increased, increasing the average score of admitted male students. There are two potential reasons for this. First, while the policy allocated, on average, 37% of seats across treated units to female students, the average proportion of female students in the post-treatment period was 33%. This indicates that not all seats were actually filled by female applicants[22]. Systematic errors in grading and finalizing admission decisions led to the admission of male instead of female test-takers. Second, it is possible that the displaced male applicants might have subsequently been admitted to the control concentrations, which might have changed the average score of the untreated concentrations in a direction similar to that of the treated units. Consequently, I could not detect significant changes in the average scores of male students at the treated concentrations. The findings show that the average gender-specific score threshold across treatment statuses was closer to the

[21] I find no significant changes in the total number of students enrolled in the treated concentrations (results not reported here). Therefore, as the number of seats available for male applicants in these concentrations is more limited than it would have been in the absence of the gender quota, one might expect the average score of male students to increase. However, this is not the case.

[22] In fact, there were systematic errors in finalizing admission decisions. In the post-quota period, in some cases, male test-takers either mistakenly or intentionally entered concentration-female specific codes in lieu of concentration-male unique codes, as seen in Figure A1.2 on their selection sheet. The administering authority used a code reader system that matched the applicants' answer sheet with the pre-programmed answer key and admitted applicants to their preferred concentration, as long as they met the score threshold. In the first few years of the quota policy, the administering authority admitted applicants without verifying their actual gender in the database; consequently, male applicants were enrolled instead of female test-takers. Nevertheless, this issue has been resolved by the NEXA authority in recent years.

minimum score, indicating a higher density of applicants in the lower tail, as shown in Table B2.1.

The strict score-based approach suggests that female applicants must score almost the same points as male Kankor test-takers to secure admission into public IHEs. Table B3.1 shows that the female-to-male students' average score ratio in the pre-treatment period was almost the same across treatment statuses. To determine whether the quota changed the composition of students within the treated concentrations, I assessed the changes in the female-to-male students' average score ratio and report the results in Column 8 of Table 2. The negative coefficient indicates that, on average, female applicants admitted into the treated concentrations had scores that were 0.04 units lower than their male counterparts, representing a 4% drop compared to the control group mean. A decrease in the score ratio suggests that the quota reduced the score threshold required for the admission of female applicants. Despite a 4% decrease in the average female-to-male student average score ratio in the short term, it may rebound in the long term. This is likely due to the indirect effects of affirmative action on improving pre-college human capital investments, as shown by Khanna (2020) and Akhtari et al. (ming). Finally, the OLS findings are robust to staggered DD estimators, as reported in Table 2, and alternative treatment specifications (major level[23]), as shown in Table B5.1.

[23]For further details about how major level analysis differ from concentration level analysis please see Data Appendix in A.4

Table 2: Effects of gender quota on outcomes at the concentration level

	Access to IHEs		Score related outcomes					
	Share females	Share females low-SES	Total avg. score	Female avg. score	High-SES female avg. score	Low-SES female avg. score	Male avg. score	Female to male avg. score ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimators								
OLS	0.09***	0.03***	-3.21*	-10.92***	-14.01***	-4.98**	-0.52	-0.04***
	(0.02)	(0.01)	(1.66)	(2.11)	(2.48)	(2.40)	(1.79)	(0.01)
Borusyak et al. (2021)$^{\varsigma}$	0.09***	0.04***	-1.15	-11.00***	-10.26***	-7.36***	1.88	-0.05***
	(0.02)	(0.01)	(1.96)	(1.98)	(2.10)	(2.01)	(2.05)	(0.01)
Sun-Abraham (2020)	0.08***	0.025***	-2.32	-9.43***	-12.53***	-3.98	0.10	-0.04***
	(0.018)	(0.006)	(1.81)	(2.19)	(2.39)	(2.87)	(1.99)	(0.007)
Concentration FE	✓	✓	✓	✓	✓	✓	✓	✓
University*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Academic pro*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Control group mean	0.28	0.10	225	224	228	221	225	0.99
N	3119	3119	3119	3119	2723	2699	3119	3119

Note: Each coefficient is from a separate regression. The dependent variables in columns 1 and 2 are the share of females and share of females from low socioeconomic backgrounds, respectively, which can be interpreted as average percentage point increase in the share of female in treated concentrations due to the quota introduction. In columns 3–7, the dependent variables are overall average score, average score for females, average score for high- and low-SES females, and male students average score at concentration level, respectively; it can be interpreted as points decrease/increase. Column 8 denotes female to male average score ratio at concentration level. All the models include stated fixed effects.

Standard errors are clustered at concentration level and reported in parentheses. Significance level: *p<0.1; **p<0.05; ***p<0.01

$^{\varsigma}$Owing to the imputing nature of the estimator by Borusyak et al. (2021), the actual number of observations used to estimate the result is slightly lower than that with the OLS and Sun-Abraham (2020). The N represents the number of observations used to compute the OLS and Sun-Abraham (2020) estimates.

6.2 Heterogeneity result

In this section, I report on the effects of the gender quota on women's access and score-related outcomes based on the competitiveness of academic programs. Table 3 presents the heterogeneity results. I classified concentrations into two groups based on the marketability and social value ascribed to these fields of study in Afghan society. Highly selective academic programs include computer science, economics, engineering, law and political science, and medicine. These are collectively known as CEELM programs[24] across public universities. The t-test differences in the main outcomes of interest between the CEELM and non-CEELM programs in the pre-2016 period is shown in Table B3.2. Notably, the share of female students and female students from low-SES backgrounds was 10 and six percentage points lower, respectively, in CEELM than in non-CEELM programs. Similarly, the average scores of matriculated applicants in CEELM programs surpassed the average scores of enrolled students in non-CEELM programs. Given the competitive nature of CEELM programs and the lower share of female students admitted to them, it is crucial to highlight the effectiveness of the gender quota on women's access to highly selective programs. Enhancing women's educational opportunities in these marketable programs is essential to close the gender gap in competitive academic programs and improve the long-term supply of qualified women in the labor force.

The impact of the gender quota on the outcomes of interest is reported in Panel A for the CEELM concentrations and Panel B for the non-CEELM concentrations in Table 3. Column 1 shows that the quota increased the share of female students in the treated CEELM concentrations by 17 percentage points, a 94% increase relative to the control group mean. Conversely, the gender quota raised the share of female students in non-CEELM concentrations by six percentage points, a 19% increase relative to the comparison group mean.

[24] Among the CEELM programs, concentrations in economics, and law and political science are not treated.

Table 3: Heterogeneous effects of gender quota on outcomes at the concentration level

	Access to IHEs		Score related outcomes					
	Share females	Share females low-SES	Total avg. score	Female avg. score	High-SES female avg. score	Low-SES female avg. score	Male avg. score	Female to male avg. score ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimators								
Panel A: CEELM								
OLS	0.17***	0.04***	-4.36	-17.94***	-21.12***	-3.65	0.88	-0.07***
	(0.03)	(0.01)	(3.46)	(5.19)	(6.43)	(7.77)	(3.23)	(0.02)
Borusyak et al. (2021)$^{\varsigma}$	0.17***	0.04***	-0.35	-18.12***	-18.06***	-9.09*	5.57	-0.09***
	(0.02)	(0.01)	(4.17)	(4.44)	(4.61)	(4.78)	(4.18)	(0.01)
Sun-Abraham (2020)	0.186***	0.045***	-1.69	-13.11**	-17.72***	-6.37	4.48	-0.06***
	(0.036)	(0.008)	(3.44)	(5.22)	(6.27)	(9.93)	(3.17)	(0.01)
Control group mean	0.18	0.05	260	259	260	256	260	1
N	748	748	748	748	688	528	748	748
Panel B: Non-CEELM								
OLS	0.06***	0.02***	-2.27	-7.84***	-10.99***	-4.88*	-0.52	-0.03***
	(0.02)	(0.01)	(1.84)	(2.14)	(2.57)	(2.53)	(2.08)	(0.01)
Borusyak et al. (2021)$^{\varsigma}$	0.05***	0.04***	-2.10	-7.80***	-6.75***	-6.64***	-0.48	-0.03***
	(0.02)	(0.01)	(1.75)	(1.87)	(2.01)	(1.87)	(1.84)	(0.01)
Sun-Abraham (2020)	0.046**	0.019**	-1.47	-6.98***	-10.61***	-3.128	-0.03	-0.03***
	(0.02)	(0.008)	(2.02)	(2.32)	(2.60)	(2.97)	(2.33)	(0.008)
Control group mean	0.31	0.12	216	215	219	214	217	0.99
N	2339	2339	2339	2339	2007	2140	2339	2339
Concentration FE	✓	✓	✓	✓	✓	✓	✓	✓
University*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Academic pro*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Highly competitive academic programs encompass concentrations within computer science, economics, engineering, law and political science, and medical studies, collectively referred to as CEELM programs. Each coefficient is from a separate regression. The dependent variables in columns 1 and 2 are the share of females and share of females from low socioeconomic backgrounds, which can be interpreted as average percentage point increase in the share of females in treated concentrations owing to the quota introduction. In columns 3–7, the dependent variables are overall average score, average score for females, average score for high- and low-SES females, and male students average score at concentration level, respectively; it can be interpreted as points decrease/increase. Column 8 denotes female to male average score ratio at concentration level. All the models in Panels A and B include the above stated fixed effects. Standard errors are clustered at concentration level and reported in parentheses. Significance level: *p<0.1; **p<0.05; ***p<0.01
$^{\varsigma}$Owing to the imputing nature of the estimator by Borusyak et al. (2021), the actual number of observations used to estimate the result is slightly lower than that with the OLS and Sun-Abraham (2020). The N represents the number of observations used to compute the OLS and Sun-Abraham (2020) estimates.

The gender quota increased the admission rate of female students from low SES by four percentage points or an 80% rise relative to the control mean in CEELM concentrations, as seen in Column 2. Meanwhile, the increase in the matriculation rate of female students from low SES in non-CEELM concentrations was two percentage points, a 16% increase compared with the control group mean.

The findings for the score-related outcomes indicate that expanding educational opportunities for women in CEELM concentrations correspond to a greater decrease in the score threshold required for admission compared to non-CEELM concentrations, as seen in Column 8 in Table 3. This trend is primarily attributed to a significant reduction in the average score of matriculated high-SES female students, as shown in Column 5. These results suggest that the gender quota is crucial to improving women's access to highly competitive concentrations, benefiting the female student population, especially those from low-SES backgrounds.

I examine the effect of the gender quota on the admissions of male applicants and their average scores from low- and high-SES backgrounds for CEELM and non-CEELM concentrations. These findings are summarized in Table 4. The quota policy allocated seats by gender without expanding the total enrollment. The overall increase in female applicants is associated with a significant displacement of male students in (non)CEELM concentrations. However, the rise in the rate of low-SES female students reported in Table 3 does not imply a significant drop in the admission rate of male applicants from low-SES backgrounds, specifically in CEELM concentrations, as shown in Column 2 of Table 4. Additionally, I do not observe significant changes in the average scores of male applicants from low- or high-SES backgrounds across CEELM and non-CEELM concentrations, as shown in Columns 3 and 4 of Table 4.

Table 4: Effects of gender quota on male students' outcomes at the concentration level

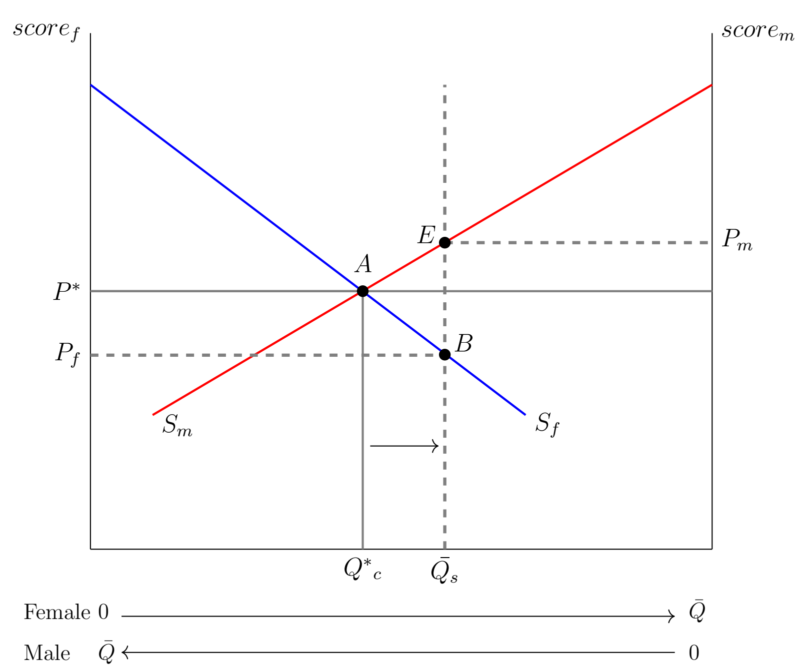
	Access to IHEs		Score related outcomes	
	Share males	Share males low-SES	High-SES male avg. score	Low-SES male avg. score
	(1)	(2)	(3)	(4)
Estimators				
Panel A: CEELM				
OLS	-0.17***	-0.04	1.20	-0.80
	(0.03)	(0.03)	(2.91)	(4.08)
Borusyak et al. (2021)$^{\zeta}$	-0.17***	-0.11***	5.64	5.76
	(0.02)	(0.02)	(4.24)	(4.07)
Sun-Abraham (2020)	-0.18***	-0.05	3.82	4.08
	(0.03)	(0.03)	(2.87)	(4.50)
Control group mean	0.82	0.39	260	259
N	748	748	748	746
Panel B: Non-CEELM				
OLS	-0.06***	-0.03*	-1.24	-0.52
	(0.02)	(0.01)	(2.07)	(2.38)
Borusyak et al. (2021)$^{\zeta}$	-0.05***	-0.04**	-1.18	-0.53
	(0.02)	(0.02)	(1.78)	(1.93)
Sun-Abraham (2020)	-0.046**	-0.02	-0.96	0.19
	(0.02)	(0.015)	(2.27)	(2.73)
Control group mean	0.69	0.41	217	216
N	2339	2339	2299	2334
Concentration FE	✓	✓	✓	✓
University*year FE	✓	✓	✓	✓
Academic pro*year FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Note: Highly competitive academic programs encompass concentrations within computer science, economics, engineering, law and political science, and medical studies, collectively referred to as CEELM programs. Each coefficient is from a separate regression. The dependent variables in columns 1 and 2 are the share of males and share of males from low socioeconomic backgrounds, which can be interpreted as average percentage point increase in the share of males students in treated concentrations owing to the quota. In columns 3–4, the dependent variables are average score for high- and low-SES male students, respectively; it can be interpreted as points decrease/increase. All the models in Panels A and B include the above stated fixed effects.
Standard errors are clustered at concentration level and reported in parentheses. Significance level: *p<0.1; **p<0.05; ***p<0.01
$^{\zeta}$Owing to the imputing nature of the estimator by Borusyak et al. (2021), the actual number of observations used to estimate the result is slightly lower than that with the OLS and Sun-Abraham (2020). The N represents the number of observations used to compute the OLS and Sun-Abraham (2020) estimates.

7 Rationale for Quota Impact

In this section, I use a supply-and-demand framework to explain why the findings correspond with the anticipated impact of a gender quota on education. This allows us to understand the underlying mechanisms driving overall and socioeconomic status-specific impacts. In Figure 2, the horizontal axis denotes the fixed number of slots available at concentrations. The left and right vertical axes indicate the required score thresholds for the admission of female and male applicants, respectively (S_f and S_m denote the supply curves for female and male applicants, respectively). In an open competition, outcome A indicates the average gender-specific proportion in a concentration, where the share of female students equals Q_c^*, and the share of male students equals $1 - Q_c^*$. The score threshold for admission is set to P^*. Hence, applicants must score at least as high as P^* to secure admission into a concentration. The gender quota acts as a quantity restriction, distributing the number of seats available according to gender. Specifically, the gender quota, on average, fixes the proportion of seats in treated concentrations for female students to $\bar{Q}_s$[25], represented by a dashed vertical line in Figure 2.

Figure 2: Effects of gender quota on admissions and score thresholds



Therefore, the quota expands the share of female students from Q_c^* to $\bar{Q}_s$. The distribution of seats can change the score threshold required for gender-specific admissions in treated concentrations. The

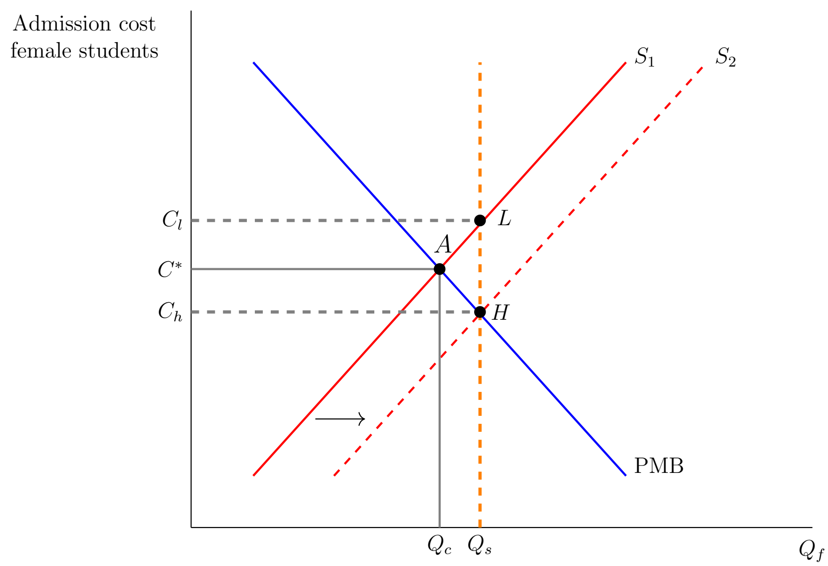
[25] On average, 37% of the available seats are reserved for female applicants in treated units.

gender quota increases the number of seats for female applicants by reducing the availability of seats for male applicants. As a result of these changes, the competition for women might be reduced, lowering the score threshold required for admission from P^* to P_f. Conversely, the score for male applicants rises from P^* to P_m. However, not all reserved slots for female applicants were actually filled by women, and male applicants matriculated in numbers greater than their allocated shares under the gender quota. These discrepancies might explain the insignificant changes in the average scores of male applicants.

One may argue that quota intervention distorts the competitive equilibrium by admitting female applicants with lower test scores who would not otherwise been enrolled. This drop in the score might lead to concerns, including a mismatch, which indicates that admitted students might not thrive academically because of preferential treatment. However, I argue that the share of female students under the competitive equilibrium ${Q^*}_c$ is below the socially optimal level. The low likelihood of admission and substantial cultural barriers can discourage female applicants from investing in human capital during the pre-Kankor period, specifically, female applicants from low SES. In Figure 3, the y-axis denotes the admission cost for female students (i.e., the time and financial investment to prepare for the Kankor exam), and the x-axis shows the number of female students matriculated in a concentration. In a competitive equilibrium, the share of female students enrolled (denoted by A) is given by the intersection of supply curve S_1 and the vertical solid line of Q_c, in which the average admission cost equals C^*.

In this state, female applicants C_l, who face higher admission costs with lower private marginal benefits (PMB), might have reduced incentives to invest in pre-Kankor human capital development. Decreased investment in pre-Kankor human capital by female applicants from low SES can exacerbate existing educational and economic inequalities. The gender quota reserved seats based on gender, moving the supply curve to S_2, in which the number of available seats for female applicants is fixed at Q_s. This level is considered a socially optimal output, with the outcomes of L and H at the extensive and intensive margins, respectively. The extensive margin enhances the enrollment prospect for female applicants from low-SES backgrounds, who face higher admission costs (e.g., limited access to Kankor preparation, social barriers, and household responsibilities) by lowering the competition level. By reducing the competition level, the gender quota potentially levels the playing field, providing applicants with a better opportunity to enroll in treated concentrations that might not previously have been considered (Fryer & Loury, 2005). Furthermore, this can encourage pre-Kankor human capital development, as shown by Khanna (2020) and Akhtari et al. (ming).

Figure 3: Low-SES female students as marginally admitted applicants



Conversely, on the intensive margin, the gender quota may likely deter incentives for a subgroup of female applicants who would have pursued these concentrations, even without the quota. This subgroup of students likely came from high-SES backgrounds and tended to have lower admission costs (e.g., greater access to Kankor preparation and fewer social barriers as they might reside in urban areas) and a higher probability of admission (e.g., receiving a better quality of education in high school). In the post-quota period, the calculation of the PMB may have been lower than that in the pre-quota period. This might be driven by the expectation that more qualified women will potentially graduate and enter the job market, increasing competition among women in the labor force. Therefore, the changes in score-related outcomes for female applicants from high SES backgrounds shed light on their responses to the adoption of the gender quota.

The gender quota in Afghanistan was introduced to broaden educational opportunities for women. This affirmative action was adopted in the anticipation that educated women would bolster economic equality, contribute to national development, and improve social welfare. Numerous studies highlight that investment in women's education can positively contribute to a country's gross domestic product (Chaaban & Cunningham, 2011), women's roles in intrahousehold financial and non-financial decisions (Le & Nguyen, 2021), and overall family and child well-being (Hill & King, 1995; Hobcraft, 1993). Additionally, such investments tend to have a higher return (Asadullah, 2006). Figure B6.1 shows that improving educational opportunities for women, especially those from low-SES backgrounds, can lead to greater social benefits, particularly in fragile settings where systematic underinvestment in women's education limits their economic and social contributions to the overall well-being of society.

8 Discussion and Conclusion

I assessed the impact of gender admission quota on women's access to Afghan public IHEs. The findings show that the quota increased gender parity in public higher education by expanding educational opportunities for women, particularly by increasing the participation rate of women from low-SES backgrounds. Moreover, the results highlight that this intervention, at least in the short term, reduced the admission score threshold for women, predominantly for applicants from high SES backgrounds. A simple supply-and-demand model can explain the mechanisms behind the expected and observed impacts of the gender quota. These findings are of significant policy importance, as this is one of the first studies to rigorously examine the impact of affirmative action on women's access to higher education in fragile and conflict-affected settings.

The gender quota policy increased the share of female applicants in the treated concentration group by 32% and the share of female students matriculated from low-SES backgrounds by 30%, relative to the control group mean. These results are consistent with the results of previous studies (Alon & Malamud, 2014; Bagde et al., 2016; Bertrand et al., 2010; de Silva et al., 2021; Mello, 2022). Additionally, I found that the gender quota almost doubled the share of female students admitted (94%) and that of female applicants enrolled from low-SES backgrounds (80%) in highly competitive academic programs. These findings are consistent with those of Bagde et al. (2016) and Vieira & Arends-Kuenning (2019).

Reducing the score threshold required for women's admission might be a source of concern, particularly regarding the academic preparation and success of matriculated applicants. This is an avenue for future research to assess the impact of the gender quota on post-matriculation outcomes[26]. However, Khanna (2020) and Akhtari et al. (ming) show that affirmative action creates prospects for marginalized groups, which, in turn, can increase minorities' schooling years and pre-college human capital investment via the enlargement of opportunities, as suggested by Fryer & Loury (2005). Therefore, expanding the matriculation rate of female students in public IHEs could have increased pre-Kankor investment among female applicants, mainly those from low-SES backgrounds. Nevertheless, if the attrition rate among matriculated female students due to the quota is higher than expected, affirmative action could be costly, as it distributes scarce educational resources without significant societal impact, as indicated by Arcidiacono & Lovenheim (2016) and Fryer & Loury (2005).

This study highlights the vital role of gender quotas in increasing educational opportunities for women in fragile and conflict-affected settings such as Afghanistan. Owing to the lack of data and recent political changes, I could not examine educational outcomes beyond the matriculation phase. Nonetheless, this

[26]I contacted various officials and entities to access student-level or concentrations-level post-matriculation outcomes with no success. The significant changes in Afghanistan since the Fall of 2021 have introduced substantial disruption in research activities.

study contributes to the growing body of literature on the role of affirmative action in reducing gender inequality. This study demonstrates that even in conflict-affected settings and heavily patriarchal societies with limited resources for human capital development, affirmative action might be a potential pathway for reducing gender inequality. However, one must recognize that preferential admission to IHEs will likely produce unintended consequences. For instance, lowering the score threshold required for admission, at least in the short term.

The return of the Taliban to power and its current ban on women's post-secondary education are reversing the progress made in women's access to post-secondary education since the beginning of the twenty-first century, especially after the implementation of the gender quota policy. Furthermore, the Taliban's ban on girls' education in secondary schools and women's participation in the Kankor exam, as of August 2023, will have a severe negative impact in the coming years. This disrupts the pipeline of applicants graduating from high school, leading to a lower rate of women eligible for the Kankor exam if the Taliban lifts the existing restrictions. Such interruptions have catastrophic consequences, as they decrease the availability of women in vital professions, especially in the health and education sectors, primarily in rural areas.[27]

[27]This is a significant setback for the country's self-reliance, as it increases dependency on international humanitarian aid. Additionally, if the Taliban pursues a gender-segregated education system but does not limit women's access to academic programs, this might increase women's participation in post-secondary education. However, this could also result in additional administrative costs. The public higher education sector has been facing significant funding issues since 2014 (Najam & Johnston, 2023), and this has been intensified by the political shocks of 2021.

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Data availability

The dataset used in this study comprises the Kankor exam results for all test-takers from 2013–2018, collected from publicly available online sources. The author compiled a six-year individual-level dataset and constructed concentration- and major-level datasets. The author is willing to make the aggregate data and the Stata codes used for analysis available online upon publication. Individual-level de-identified data can be shared on a case-by-case basis. Computational reproducibility verified by DIME Analytics. Please see details of the reproducibility in the online appendix or this LINK.

Disclosure statement

None

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT-4 in order to identify grammatical errors in some sections of the draft version of the paper before rigorous proofreading. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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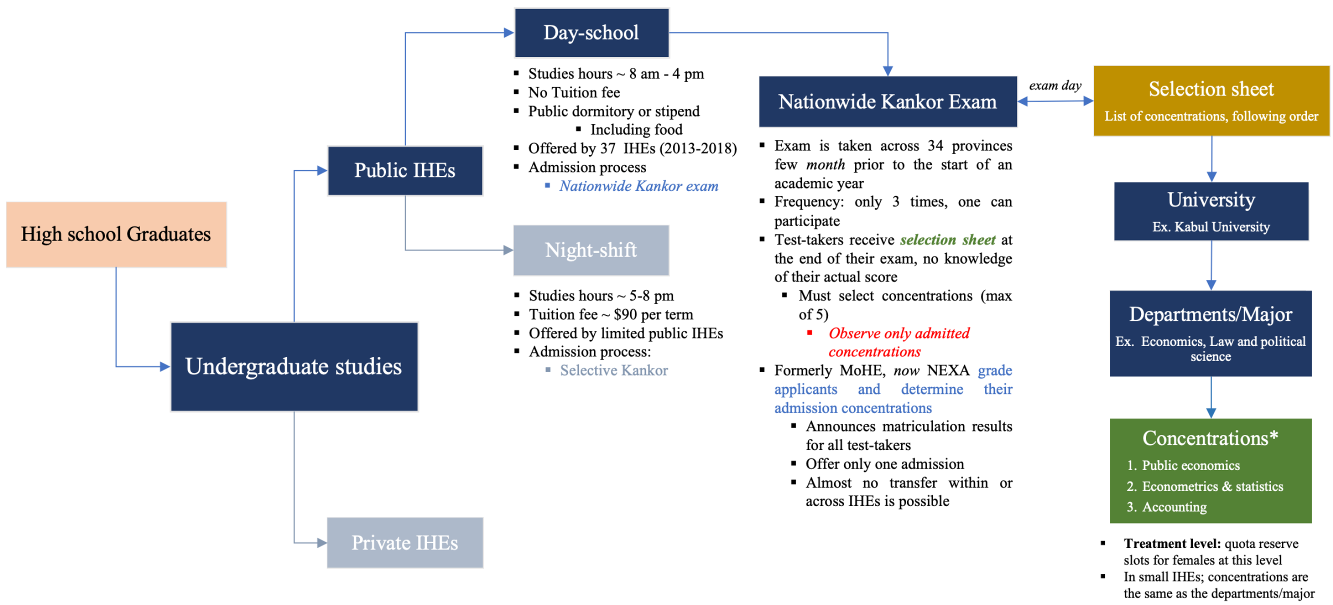
A Appendix A: Context

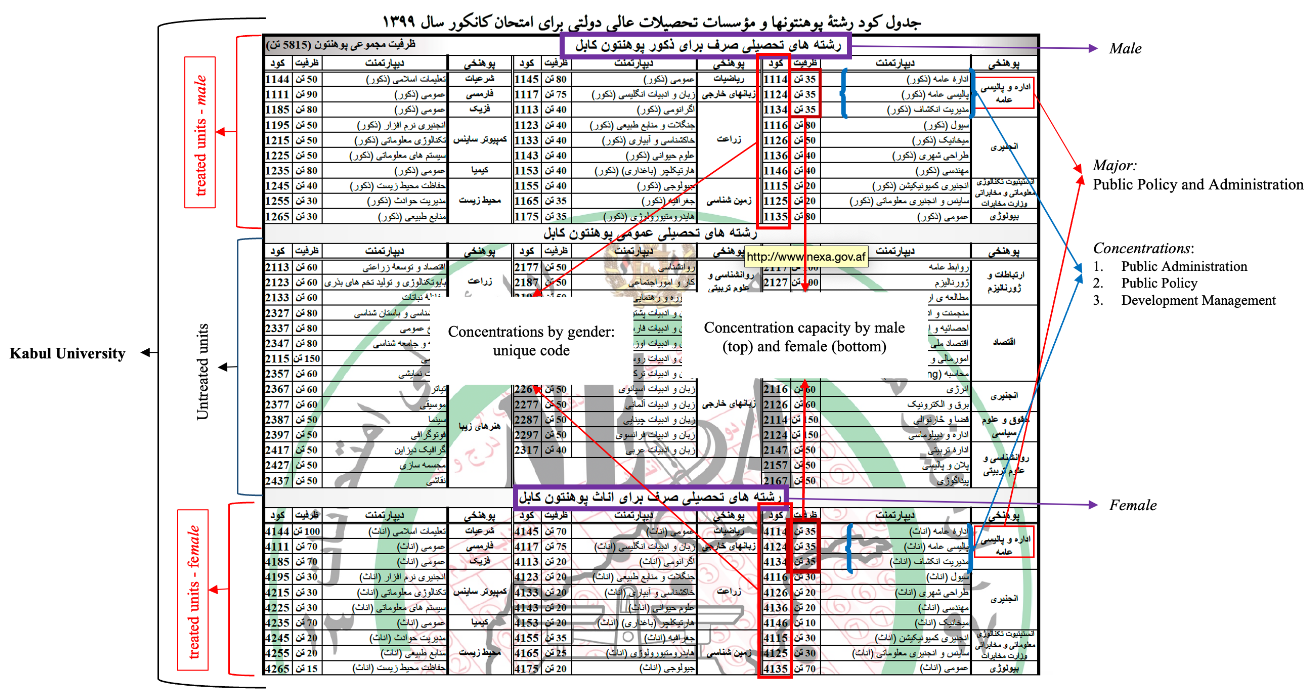
A.1 Admission and Selection Sheet

Figure A1.1: Admission process in Afghan public universities



Note: The figure created by the author highlights the admission process for public higher education in Afghanistan.

Figure A1.2: Kankor concentrations selection sheet



Note: The selection sheet shows enrollment capacity by university-concentrations, with gender-specific codes for the treated units.

A.2 Conceptual differences

Table A2.1: Conceptual differences: Concentration, major, academic program, and university

Concentration (1)	Major (2)	Academic program (3)	University (4)
Econometrics_KU	Economics_KU	Economics	Kabul University (KU)
BBA_KU	Economics_KU	Economics	Kabul University (KU)
Econometrics_BU	Economics_BU	Economics	Balkh University (BU)
BBA_BU	Economics_BU	Economics	Balkh University (BU)
Agronomy_KU	Agriculture_KU	Agriculture	Kabul University (KU)
Agribusiness_KU	Agriculture_KU	Agriculture	Kabul University (KU)
Agronomy_BU	Agriculture_BU	Agriculture	Balkh University (BU)
Agribusines_BU	Agriculture_BU	Agriculture	Balkh University (BU)

Note: Concentrations are unique level of enrollment. The 'major' identifies the parent department of concentrations within a university in 2013. An 'academic program' refers to a universal grouping of concentrations across different universities. The Column 4 denotes university unique identifier."

A.3 List of universities and academic programs

Table A3.1: Total number of concentrations and share of treated concentrations by university

	Number of concentrations	% ever treated
Al Beroni University (AU)	31	32
Badakhshan University (BDU)	29	24
Badghis Higher Education Institution (BADU)	14	0
Baghlan University (BGU)	34	0
Balkh University (BU)	67	39
Bamyan University (BAU)	40	40
Daykundi Higher Education Institution (DKU)	9	0
Farah Higher Education Institution (FRU)	12	0
Faryab University (FU)	32	0
Ghazni Technical Engineering University (GTU)	2	0
Ghazni University (GU)	20	0
Ghor Higher Education Institution (GRU)	13	0
Helmand Higher Education Institution (HLU)	13	0
Herat University (HU)	69	32
Jawzjan University (JU)	46	0
Kabul Polytechnic University (KPU)	23	100
Kabul University (KU)	82	39
Kabul University of Medical Sciences (KUMS)	10	90
Kandahar University (KDRU)	40	28
Sayed Jamaluddin Afghani/Kunar University (KUU)	22	0
Kunduz University (KNU)	33	0
Laghman University (LU)	20	0
Logar Higher Education Institution (LGU)	6	0
Nangarhar University (NU)	58	38
Nimrooz Higher Education Institution (NMU)	4	0
Paktia University (PU)	33	30
Paktika Higher Education Institution (PKU)	12	0
Panjshir Higher Education Institution (PNU)	12	0
Parwan University (PRU)	32	0
Samangan Higher Education Institution (SU)	19	0
Sar-e-pul Higher Education Institution (SPU)	8	0
Shahid Professor Rabani Education University (SREU)	34	0
Shaikh Zayed University (SZU)	40	38
Takhar University (TU)	38	0
Urozgan Higher Education Institution (UU)	11	0
Maidan Wardak Higher Education Institution (WU)	3	0
Zabul Higher Education Institution (ZU)	4	0
Total	975	21

Source: Kankor matriculation dataset 2013-2018.

Table A3.2: Total number of concentrations and share of treated concentrations by academic program

	Number of concentrations	% ever treated
Agriculture	136	23
Computer Science	37	51
Economics	73	0
Education	274	12
Engineering	73	49
Geology and Environmental studies	33	61
Islamic Studies	26	0
Journalism	29	0
Law and Political Sci	46	0
Literature	95	5
Medical Studies	23	83
Psychology	13	0
Public Administration and Policy	16	100
Science Education	16	81
Social Science	63	11
Technician (e.g., chemical tech, food tech)	9	44
Veterinary	12	0
Total	975	21

Note: Author created the academic programs according to the NEXA selection sheet classification.
Source: Kankor matriculation dataset 2013-2018.

A.4 Data appendix

The labels for concentrations in the Kankor dataset are in local languages (Dari and Pashto) with variations over time. Therefore, to create a panel dataset at the concentration level, first, I took the 2013 dataset and assigned a unique English label to each concentration, which I entered in the subsequent years for the same concentration. The assigned labels include university abbreviations to identify university-unique concentrations.

As shown in Table B1.1, the number of concentrations increases over time. This increase is due to the disaggregation of admission in some units of study–from general to concentration level. Consequently, whenever a new concentration was established in the year following 2013, it is coded as a new observation(s). The unit of studies in 2013 serves as a baseline, allowing for tracking the units of study and identifying if a particular major/department disaggregated admission into multiple segments in the years after 2013. New concentrations are entered under a new label and the former label—general-level admission indicator—is not entered. For example, let us consider that the Public Policy and Administration (PPA) department at Kabul University had a general admission process for the years 2013–2016 academic years but disaggregated its admission across three concentrations in 2017–2018. The data structure for observing these concentrations in the dataset is shown in Table A4.1. The data for this unit of study are entered under the general admission label (PA KU) for 2013–2016, and as unique units of study for 2017–2018. Therefore, in the concentration dataset, the enrollment level by year is taken at its face value, as shown in Table A4.1.

Furthermore, I also created an alternative treatment specification for the matriculation dataset–major level. I aggregated enrollment data at the unit of study level for the baseline year (2013) into a single observation in the dataset. This process essentially reverses the disaggregation process, ensuring consistent labeling under their parent major over time. This produces a balanced panel dataset. For

Table A4.1: Tracking changes in admission level

Original concentration label (1)	assigned English label (2)	General (3)				Concentration (4)	
		Year					
		2013	2014	2015	2016	2017	2018
Public Administration and Policy	PA KU	1	1	1	1	x	x
Public Administration	PA_dep_PA KU	x	x	x	x	1	1
Public Policy	PP_dep_PA KU	x	x	x	x	1	1
Development Management	Dev_manag_PA KU	x	x	x	x	1	1

Note: 1 if a concentration is observed in a given year in the dataset, X otherwise.

example, I aggregated the admission of the three concentrations for Public Policy and Administration (PPA) in the years 2017–2018, as shown in Table A4.1, to its parent level and entered it as a single unit of observation in the major level dataset, as shown in Table A4.2.

Table A4.2: Reversing concentrations level admission into major level

Major/Department label (1)	Assigned English label (2)	year					
		2013	2014	2015	2016	2017	2018
Public Administration and Policy	PA KU	1	1	1	1	1	1

Note: Concentrations are being reverted to their parent majors according to the unit of study in 2013.

The aggregation to major level poses a new challenge. In some cases, only a few concentrations within the major might have adopted the policy. Thus, a major is considered treated as long as more than 1/3 of its concentrations adopted the policy. This is an arbitrary decision by the author to differentiate between treated and untreated units in the major dataset. Nevertheless, concentration level analysis remains the main specification, as it is the primary treatment level.

B Appendix B: Empirical Tables

B.1 Yearly statistics

Table B1.1: Descriptive statistics for Kankor participants by year

	2013	2014	2015	2016	2017	2018
Number of concentrations	242	388	590	608	763	768
% ever treated concentrations	22	23	25	26	25	25
Total Kankor participants in *thousands*	181.02	231.15	228.23	182	169.64	159
% female	30	34	32	32	33	34
% matriculated into 4-year public IHEs	28	24	24	31	35	37
% of female among matriculated	21	22	26	25	29	32
Overall Average score	201	199	193	178	180	180

Source: Kankor matriculation dataset for 2013-2018.

B.2 Gender-specific score distribution

Table B2.1: Gender-specific score distribution across treatment status for pre- and post-2016

	control			treated		
	average score	min	max	average score	min	max
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female students						
Pre-2016	264.55	248.18	294.63	286.53	273.72	307
Post-2016	200.21	190.06	224.47	219.19	204.34	251.14
Panel B: Male students						
Pre-2016	266.35	246.66	308.14	287	271.11	319
Post-2016	201.49	188.63	242.10	234.01	214.69	273.62

Note: The results show that the average gender-specific score across treatment status is closer to the minimum score, indicating a higher density of applicants in the lower tail. I chose 2016 as the point of temporal division because approximately 85 percent of the treated concentrations adopted the policy in 2016.

B.3 Pre-treatment balance based on treatment status and CLEEM status

Table B3.1: Balance-test for pre-2016 outcomes by treatment status

	Control (1)	Treated (2)	Difference (3)	P-value (4)
Share of female	0.26	0.22	-0.04	0.002
Share of female from low-SES	0.09	0.04	-0.05	0.000
Total avg. score	266	287	21	0.000
Female avg. score	265	287	22	0.000
High-SES female avg. score	266	289	23	0.000
Low-SES female avg. score	262	281	19	0.000
Male avg. score	266	287	21	0.000
Female to male avg. score ratio	0.992	0.998	0.005	0.008

Source: Kankor matriculation dataset for 2013-2015. I chose 2016 as the point of temporal division because approximately 85 percent of the treated concentrations adopted the policy in 2016.

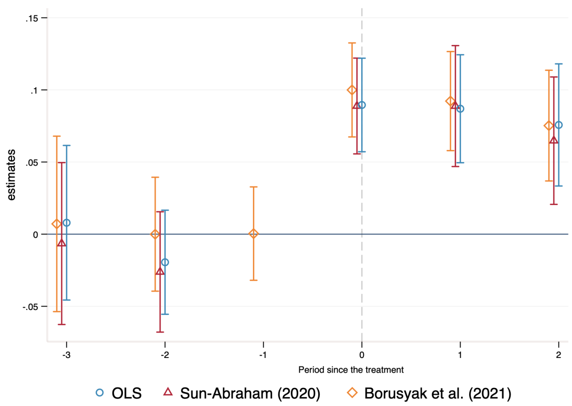
Table B3.2: Balance-test for pre-2016 outcomes by CEELM status

	Non-CEELM (1)	CEELM (2)	Difference (3)	P-value (4)
Share of female	0.28	0.17	-0.11	0.000
Share of female from low-SES	0.09	0.03	-0.06	0.000
Total avg. score	259	302	44	0.000
Female avg. score	258	302	45	0.000
High-SES female avg. score	260	304	44	0.000
Low-SES female avg. score	256	301	44	0.000
Male avg. score	260	303	43	0.000
Female to male avg. score ratio	0.99	1	0.01	0.000

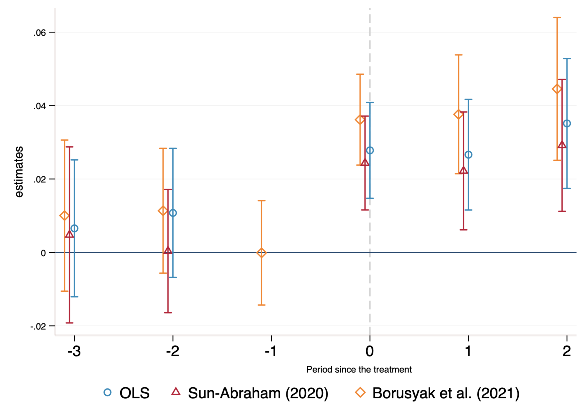
Note: Highly competitive academic programs encompass concentrations within computer science, economics, engineering, law and political Science, and medical studies, collectively referred to as CEELM programs. I chose 2016 as the point of temporal division because approximately 85 percent of the treated concentrations adopted the policy in 2016.

B.4 Event Study - outcomes at concentration level

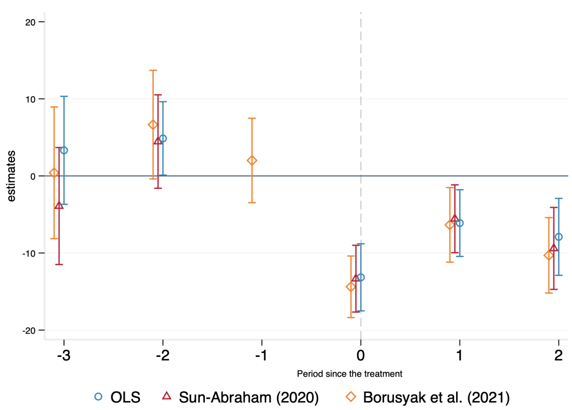
(a) Share of female students



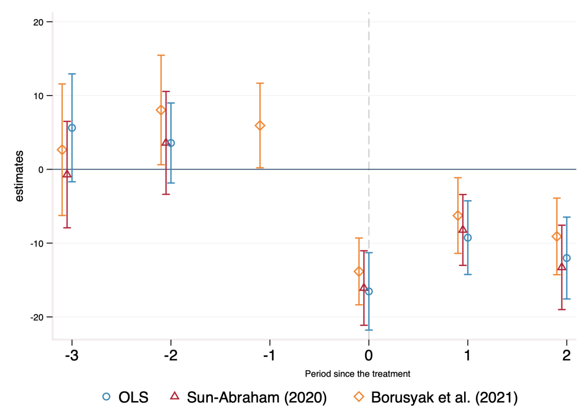
(b) Share of female students from low-SES



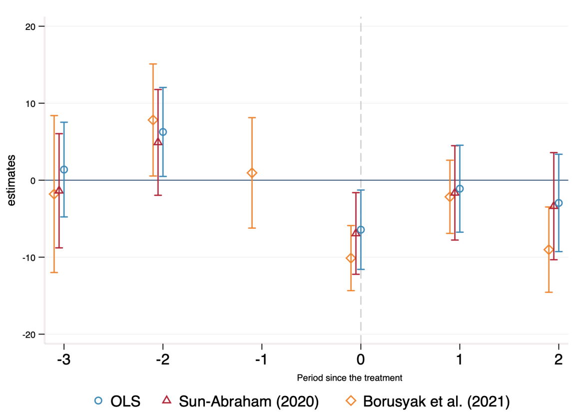
(c) Female students avg. score



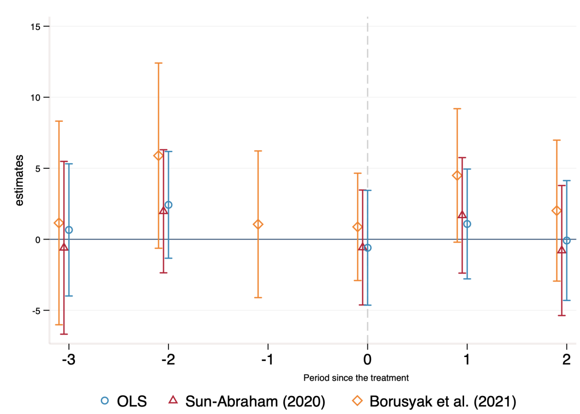
(d) High-SES female students avg. score



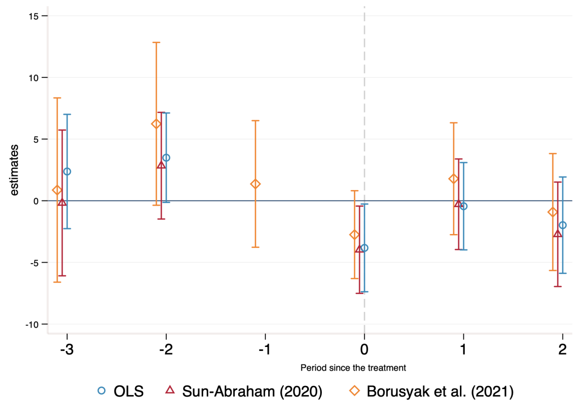
(e) Low-SES female students avg. score



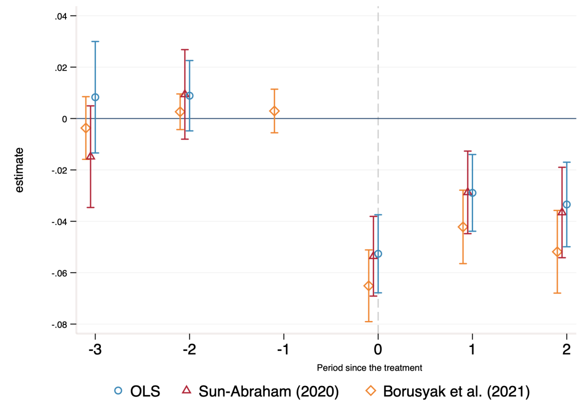
(f) Male students avg. score



(g) Total students avg. score



(h) Female to male applicants avg. score ratio



Note: The above figures report the event study coefficients based on Equation 2 for the outcomes, such as the share of females, share of low-SES females, female average score, high- and low-SES female average score, male average score, total average score, and the female to male average score ratio at concentration level. These coefficients are calculated using three specifications - OLS, Borusyak et al. (2022), and Sun & Abraham (2021). The y-scale value varies across figures. The coefficient represents the change in outcomes for the treated units compared to the untreated units in the years before and after the implementation of quota in public universities in Afghanistan. The reference year is t-1, and year 0 refers to the time when a particular concentration adopted the policy. The leads lower than -3 are combined owing to the low number of observations. These figures provide evidence of parallel trends in the pre-quota period and insights about the dynamic impact of quota policies on various outcomes in the post-treatment period.

Owing to the imputing nature of the estimator by Borusyak et al. (2021), the actual number of observations used to estimate the result is slightly lower than that with the OLS and Sun-Abraham (2020). The number of observations N for the OLS and Sun-Abraham (2020) estimates are the same.

B.5 Robustness: Major level result

Table B5.1: Effects of gender quota on outcomes at *major level*

	Access to IHEs		Score related outcomes					
	Share females	Share females low-SES	Total avg. score	Female avg. score	High-SES female avg. score	Low-SES female avg. score	Male avg. score	Female to male avg. score ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimators								
OLS	0.07***	0.02**	-5.29***	-9.32***	-8.00***	-6.21**	-3.36	-0.02***
	(0.02)	(0.01)	(1.93)	(2.36)	(2.81)	(2.62)	(2.05)	(0.01)
Borusyak et al. (2021)$^{\zeta}$	0.11***	0.06***	-4.96*	-11.72***	-11.73***	-8.63***	-1.90	-0.04***
	(0.02)	(0.01)	(2.77)	(3.23)	(3.28)	(3.17)	(2.80)	(0.01)
Sun-Abraham (2020)	0.06**	0.016	-3.81	-8.25***	-6.97**	-4.90	-2.44	-0.02**
	(0.02)	(0.01)	(2.61)	(3.12)	(3.33)	(4.09)	(2.69)	(0.01)
Major FE	✓	✓	✓	✓	✓	✓	✓	✓
University*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Academic pro*year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Control group mean	0.29	0.09	238	237	239	235	239	0.99
N	1623	1623	1623	1623	1522	1465	1623	1623

Note: Each coefficient is from a separate regression. The dependent variables in columns 1 and 2 are the share of females and share of females from low socioeconomic backgrounds, which can be interpreted as average percentage point increase in the share of females in treated majors due to the quota introduction. In Columns 3–7, the dependent variables are overall average score, average score for females, average score for high- and low-SES females, and male students average score at major level, respectively, it can be interpreted as points decrease/increase. Column 8 denotes the female to male average score ratio at major level. All the models include stated fixed effects.
Standard errors are clustered at major level and reported in parentheses. Significance level: *p<0.1; **p<0.05; ***p<0.01
$^{\zeta}$Owing to the imputing nature of the estimator by Borusyak et al. (2021), the actual number of observations used to estimate the result is slightly lower than that with the OLS and Sun-Abraham (2020). The N represents the number of observations used to compute the OLS and Sun-Abraham (2020) estimates.

B.6 Social implication of Gender Quota

Figure B6.1: Social implication of gender quota

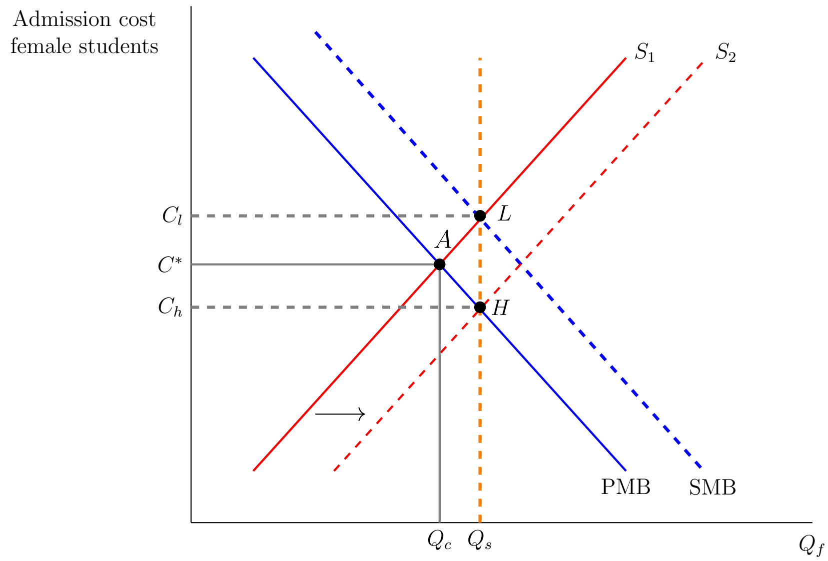


Figure B6.1 highlights the importance of quota intervention in increasing educational opportunities for women. Quotas can overcome the higher admission costs that women often face, leading to greater social benefits, such as improved health, education, and economic growth. This additional benefit can be shown by the increase in social marginal benefit.