The Labor Market Returns to Unobserved Skills: Evidence from a Gender Quota*

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December 13, 2022

Abstract

We estimate the effects of unobserved skills on labor market outcomes by investigating a change in the distribution of unobserved skills. Among people with the same levels of observed skills such as education and work experience, there are still disparities in labor market outcomes. since employers cannot observe all applicantsâ skills and productivity, they rely on the average skills of different groups. We exploit a discontinuity generated by the 2012 education policy in Iran. This policy restricting female students in specific college majors changes the size and skill distribution of high school graduates. We find three main findings. First, the education quota lowers women's college attendance. Second, young high-school graduate women are more likely to participate in the labor market and have a job. Third, the gender wage gap decreases among high-school workers due to both within and between occupation changes: treated women are paid more and they take up higher-paying middle-skilled positions that used to be non-traditional occupations for them.

Keywords: Unobserved Skills; Occupational Choice; Education Quota; Gender Discrimination; Wage differentials.

*This paper is previously circulated under the title "Education Quota: The Effects of Quality and Quantity of Labor Force". We wish to thank Josefa Aguirre, Cassandra Benson, Smriti Bhargava, Jo Blanden, Alessandra Gonzalez, Sermin Gungor, Jean-William Laliberté, Thomas Lemieux, Joniada Milla, Christine Neill, Miana Plesca, Gema Zamarro Rodriguez, Kevin Schnepel, and Leslie Stratton for their helpful feedback. We are grateful to Sepehr Ekbatani for providing demographic information of applicants of 2012 university entrance exam. We also benefited from feedback by conference participants at the 2022 and 2021 Canadian Economics Association, 2021 Southern Economics Association, and Canadian Women Economist Committee seminar. Any omissions or errors are our own responsibility.

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1 Introduction

Labor market outcomes depend on both the demand and supply of skills. As demonstrated by Lemieux (2006), income inequality is largely explained by education and experience. Additionally, personality attributes like persistence and self-esteem are equally or more important than cognitive abilities in explaining earning variation and other life-time outcomes including educational attainment, occupation choice, and productivity.[1] Still, the gaps in employment opportunities and wage rates remain among people with the same level of observed skills, leaving the questions on the effects of the unobserved skills widely open.[2] In this paper, we identify the effect of unobserved skills on labor market outcomes, separate from that of observable skills. To do so, we investigate the impact of an exogenous shock on the skills distribution among high-school workers.

The central empirical challenge of estimating the effects of skills on labor market outcomes is selection bias and correlation between different skills. For example, personality factors have a major effect on schooling and occupation choices, and cognition plays a significant role in personality formation (Heckman et al., 2006; Borghans et al., 2008; Caponi and Plesca, 2009; Heckman and Raut, 2016; Humphries and Kosse, 2017). The ideal analysis would involve a controlled experiment in which a specific skill is randomly assigned across individuals. Current literature use such randomized interventions to find the labor market return of observed skills.[3] However, observed skills cannot explain the total gap in labor market outcomes. The unexplained part may be the result of skills that are not observable. A common approach to address this problem is providing better measures for cognitive and non-cognitive skills and using them as proxies for unobserved skills. However, not only are skill measures prone to measurement error and imperfect proxies (Heckman et al., 2006),[4] but also some skills remain unobservable, no matter how rich the data are (Buchmueller and Walker, 2020). We complement this literature by estimating the labor market return of unobserved skills without the need to rely on proxies. Our approach takes advantage of a gender quota that provides a variation in unobserved skills of workers with similar observables (education, age, etc.).

We overcome the selection problem by using discontinuities in college admission generated by a

[1]For more on the effects of personality attributes on life-time outcomes, see Bowles et al. (2001); Heckman et al. (2006); Borghans et al. (2008); Castillo et al. (2011); Lindqvist and Vestman (2011); Heckman and Kautz (2012); Fletcher (2013); Heckman et al. (2013); Krishnan and Krutikova (2013); Golsteyn et al. (2014); Kautz et al. (2014); Hanushek et al. (2016); Heckman and Raut (2016); Cubel et al. (2016); Edin et al. (2017); Alan et al. (2019) and Saltiel (2020).

[2]While most difficult-to-observe skills are in the nature of noncognitive, some aspects of cognitive skills (e.g., quality of education) remain unobservable.

[3]A group of recent studies use randomized interventions to cognitive skill (e.g., college education (Zimmerman, 2014), quality of education (Anelli, 2020), and college major (Bertrand et al., 2010)) or a non-cognitive skill (e.g., soft skills (Bassi and Nansamba, 2022), patience (Alan and Ertac, 2018), and grit (Alan et al., 2019)). The results of these studies are limited to the effect of specific observed skills that are targeted by the intervention. Another stream of literature use twin data to address endogeneity. Genetic differences between twins are random and remain fixed over the lifetime, thus causal effects can be demonstrated (Lindqvist and Vestman, 2011; Buser et al., 2021). However, as psychological studies find, even identical twins are differently affected by environmental factors; 70% of personality change and 20% of the variation in stable component of personality traits are determined by non-genetic factors (Borghans et al., 2008).

[4]For example, years of schooling (a common measure of education) does not consider the quality of education. Also, non-cognitive skills are usually assessed by self-reported questionnaires or performance on some tasks that depends on multiple skills, as well as incentives (Kautz et al., 2014).

gender quota in 2012 in Iran. In August 2012, Iran's Ministry of Science, Research and Technology announced restrictions on university entry for female students. This restriction makes some majors male-only and sets a cap for female students in many other majors. Therefore, young women and men who completed high school after 2012 faced different education opportunities than older women and men did. This policy generates quasi-experimental variation for identifying unobserved skills effects on labor market outcomes of high-school graduates who never went to college (HSG). We limit our sample to the population of HSGs because, as Arcidiacono et al. (2010) shows, for college graduates, skills are almost perfectly observable upon entering the labor market, but for HSGs, it takes more time to be revealed. Thus, unobserved skills have more important role in labor market outcomes of HSGs, in particular for women (Nielsson and Steingrimsdottir, 2018).[5]

The theoretical prediction for the effect of this policy on labor market outcomes of HSGs is ambiguous. Employers can not identify workers' productivity. They can observe schooling, work experience, etc., but not unobserved skills and whether an individual was constrained from entering university;[6] they therefore pay HSG workers the average productivity (skill). On the one hand, the quota may not have any effects on labor market outcomes of HSGs because observed skills of compliers (young women who were not admitted but would have been in the absence of the quotas) are similar to other HSG workers. On the other hand, the quota may affect labor market outcomes of HSGs by changing employers beliefs about the average productivity of workers. The quota may affect the size and the skill distribution of HSGs by selecting different individuals for college. In particular, inflow of compliers to and outflow of defiers (young men who were admitted but would not have been in the absence of the quota) from the population of HSGs can change the skill pool of HSGs. Employers, who are aware of the quota, would expect an increase in the mean skill level of young women HSGs, and thus may be more willing to hire young women. Therefore, the overall effect of the quota on labor market outcomes depends on two factors: one is whether the quota has any effect on the distribution of unobserved skills among HSGs, and the other one is whether unobserved skills have any meaningful effect on labor market outcomes. Thus, we first examine the effect of the quota on skill distribution of HSGs by estimating changes in female and male college enrollment. Second, we ask whether and how changes in skill distribution of HSG workers affect their labor market outcomes.[7]

[5]We limit our sample to individuals with similar observables to isolate the effect of unobserved skills. Notice that individuals in the total sample have different observed skills (e.g., different education level). In fact, the only change the policy made in the total population is a shock in education level (an observed skill). A large body of literature estimate the returns to education by exploiting affirmative action programs in higher education, see for example Bertrand et al. (2010), Öckert (2010), Zimmerman (2014), and Ozier (2018).

[6]Since the university exam score is not observable to employers and us, distinguishing complier and never takers (women who never go to university regardless of the quota) is not possible.

[7]The idea is similar to the approach used in the literature on the effects of immigration on labor market outcomes. As these studies show, effects of immigration on the local economies' labor markets depend on the structure of an economy, as well as changes in the size and skill distribution of the labor force (Dustmann et al., 2005; Manacorda et al., 2012; Pandey and Chaudhuri, 2017). Most of these studies find no or positive spillover effect on natives' wage rates mostly because either skill distribution of immigrants is similar to that of the native born workers or firms response by changing production technologies. Unlike these studies that focus on observed skills such as education and working experience, we investigate a change in unobserved skills distribution and find the effects on labor market through the lens of labor force participation, wage rate, and occupational change within and cross gender.

We implement a regression discontinuity (RD) design method that exploits the discontinuity in college enrollment across birth cohorts among high-school graduates. The birth cohorts are separated by the birth year and month threshold, September 1992. We define high-school graduates who are born after the threshold as the treated group and those born before the threshold as the control group. Our analysis shows that the September 1992 birth date threshold satisfies all the conditions for the implementation of an RD design. First, there are no other policies based on this birth-month threshold or implemented around August 2012. Also, the quota was unexpectedly announced when university applicants were going to submit their applications. Second, in addition to being exogenous, the birth date is highly correlated with the timing of high school graduation.[8,9] Third, we find no significant discontinuities in covariates.

Our empirical results using nationally representative data from the 2006-2018 Iranian Labor Force Survey (ILFS) show that the quota reduces women's college attendance rate by 2.5 percentage points (from pre-treatment average of 55%). However, we find no evidence of significant positive effects for men. One possible explanation for the insignificant change in men's college enrollment is that they are not willing to be associated with a sorority, as the quota reserves a significant number of seats for men in education and humanities which are female-dominated majors. In 2011 (the year before the quota), women made up 70% and 80% of first-year students in education and humanities, respectively. As Table 1 shows, despite a 30% quota reserved for male students in these majors, share of male students remained unchanged in 2012 because male candidates did not apply to these majors.

Next, we examine the labor market outcomes of high school graduates who never attended college. Our results show that the affected HSG women, who are restricted by the quota from attending college, are more likely to participate in the labor market and have a job by 3 pp compared to control HSG women. Conceptually, it is unclear whether this change in labor supply has any meaningful effects on wage rates. On the one hand, this increase in the relative supply of young HSG women may decrease their wage rates (change in the size). On the other hand, this group of women may have higher productivity than their male and older female counterparts and hence be paid higher wage rates (change in the skill distribution). It is worth mentioning that we cannot disentangle them empirically. Thus, since these two channels may offset each other's contribution to the wage rates, our results will be an underestimation of the effect of unobserved skills on the wage rates. Our results show that young HSG female workers' wages significantly increase (by 0.5%) and there is no significant effect on men's wage rate. Thus, the gender wage gap narrows among HSG workers. There are at least two potential explanations for the

[8]Because of age restriction in the education system (Ministry of Education), most Iranian students from the same birth cohort graduate from high school at the same time, as it is not possible to postpone graduation for several years or getting back to school at older ages.

[9]A fuzzy regression discontinuity design seems more appropriate identification. However, we do not observe the graduation date in our data. Still, since our data is a two-year rotating panel, we can estimate the graduation date for a subsample of the data. We apply a fuzzy RD design using this subsample and a discontinuity across birth date in the probability of facing lower educational opportunities (graduating from pre-university after the policy). However, we do not use fuzzy RD as the main approach because of our data limitation. Due to low female labor force participation, this subsample is relatively small for studying labor market outcomes, and thus our robustness checks are not powerful enough.

reduction in the gender wage gap among HSG workers: treated women receive higher wages than their counterparts in the same occupation and/or treated women may take on higher-paying jobs. Our results provide evidence of both within and between occupation changes in the wage rates. In particular, we find that treated women enter the workforce as technicians and service workers in the manufacturing, professional, and other service sectors, where employees are paid substantially more. These positions have traditionally been occupied by men and experienced older women. Treated young women who get these higher-paying middle-skilled positions without any experience, may displace young males, older males, and/or older female workers. If this is the case, whom do these young women substitute for in the labor market? Our estimates of the elasticity of substitution between HSG workers in different birth cohorts and gender groups show that in the production process, young and older cohorts are substitutes ($\sigma_C = 10.2$), but female and male workers are complements ($\sigma_S = -2.8$). While their entrants drive older female incumbents out of the labor market, it has no effect on men. One possible explanation for this finding is occupational segregation by gender. Our results show that occupations are moderately gender-segregated among HSG workers; the occupational gender segregation index is around 0.5. Although there is a reduction in occupational segregation (from 0.55 to 0.52), occupations are still gender-segregated, which can reflect the importance of gender balance in the workplace for employers.

Overall, HSG women who are prevented from going to college enter the labor market, which changes the size (quantity) and skill distribution (quality) of HSG workers. Treated HSG women not only are successful to find employment but also take up higher-paying middle-skilled positions that used to be non-traditional occupations for them. Such changes in the labor market narrow the gender wage gap among HSG workers. This finding highlights the role of occupational choice on gender inequality in the labor market. We provide a large set of robustness checks that confirm the causal interpretation of our findings. We also examine the heterogeneous effects using policy intensity. We find that a one-percentage-point decrease in the proportion of female college students results in a 0.1-0.3 percentage point increase in women's labor force participation and employment propensity, and a 0.5-0.6 percentage point reduction in their unemployment rates.

Beside identifying causal effects of unobserved skills on labor market outcomes, our study complements the literature in two significant aspects. First, this paper contributes to the literature on gender inequality in the labor market and the role of employers' beliefs on the productivity of worker groups. Our results highlight the importance of statistical discrimination and show how credible information affects it. Despite the increasing participation of women in the labor force, the labor market outcomes of women differ from those of men. The current literature document different factors of the gender gap on the demand and supply sides.[10] In particular, a lower wage rate among women with similar observed skills as their male counterparts can be interpreted as gender-biased beliefs among employers (Goldin and Rouse, 2000; Black and Strahan, 2001; Reuben et al., 2014; Landsman, 2018; Lesner, 2018; Bordalo et al., 2019). In particular, since employers cannot observe applicants' productivity, they rely on the

[10]Including differences in productivity (Mulligan and Rubinstein, 2008; Bartolucci, 2013), preferences (Card et al., 2016; Sin et al., 2017), labor market discrimination (Morchio et al., 2019), and policies (Blau and Kahn, 2017; Bertrand et al., 2019).

average productivity of different groups, for example gender or race. Current studies show these beliefs can change as employers learn about individual productivity through their hiring (Altonji and Pierret, 2001; Lange, 2007; Arcidiacono et al., 2010; Kahn and Lange, 2014). Lepage (2020) shows employers also learn about group productivity based on their own hiring experiences with workers from different groups. Our results provide evidence of employers learning and updating beliefs about productivity of a group prior to hiring. The source of information in our case is the 2012 quota. It is reasonable to assume that employers were informed about the quota. Our results provide evidence of both within and between occupation changes in the women's wage rates, supporting the idea that employers update their beliefs about HSG women's skills after the quota is implemented, as they know there are some high-ability young HSG women who did not enter the college only because the quota prevented them.[11] Our results suggest that policies that reduce information fractions about minorities' productivity, can improve their labor market outcomes and decrease statistical discrimination. Also, our findings consistent with a signaling model and reject a pure human capital model.[12] While a pure human capital model predicts a reduction in labor market outcomes of compliers to those of other HSG workers, signaling model allows for the possibility that compliers achieve higher outcomes than other HSG workers if they can distinguish themselves.

Second, our paper relates to the literature on education quotas and affirmative action policies. Affirmative actions are intended to help minorities and disadvantaged groups. In particular, education quotas in higher education promote equity in university admissions for individuals of all genders, races, and socioeconomic statuses. Recent studies examine admission quotas, which reserve a specific percentage of spots for the underprivileged students, to evaluate the efficiency and effectiveness of a quota system (Loury and Garman, 1993; Holzer and Neumark, 2000; Arcidiacono, 2005; Holzer and Neumark, 2006; Rothstein and Yoon, 2008; Bertrand et al., 2010; Francis and Tannuri-Pianto, 2012; Bagde et al., 2016; Cassan, 2019). Also, several studies investigate the effects of eliminating affirmative action on the college enrollment of minority students (Conrad and Sharpe, 1996; Long, 2004; Card and Krueger, 2005; Dickson, 2006; Hinrichs, 2012; Antonovics and Backes, 2014; Yagan, 2016). Due to the scarce incidence of ceiling policies like the 2012 gender quota, to the best of our knowledge, this is the first paper to estimate the effect of an education ceiling on a disadvantaged group. Our paper complements this literature in two dimensions. First, we provide evidence of the symmetric effects of positive and negative shocks to education opportunities on education. Second, while most current studies focus on labor market outcomes of defiers, we estimate the effects on the compliers.

This paper proceeds as follows. In section 2, we introduce the institutional setting (Iranian education system and the 2012 gender quota). In sections 3 and 4, we discuss the data and the identification strategy. We present and discuss the main empirical results on education and labor market outcomes in

[11] Another explanation for the gender gap in labor market outcomes is gender differences in occupational self-selection on the supply side (Polachek, 1981; Azmat and Petrongolo, 2014; Strain and Webber, 2017; Azmat and Petrongolo, 2014). Although, distinguishing these two channels is empirically challenging, we used information on working preferences of unemployed individuals in our data and provide evidence of no changes in women working preferences.

[12] Returns to education is the result of raising in labor productivity (human capital model of Becker 1962; Schultz 1961) and/or signaling of higher unobservable ability to employers (signaling model of Arrow 1973; Spence 1978).

section 5, and conduct the robustness check in section 6. This is followed by section 7 which explores heterogeneous effects by exposure to the quota. Section 8 concludes the paper. All appendix materials can be found in the Online Appendix.

2 Background

2.1 Iranian Education System

The pre-college schooling system in Iran offers twelve years of education. Before going to college, Iranian students spend their first five years of schooling in primary school, followed by six years in high school (three years lower-secondary and three years upper-secondary). Since upper-secondary education is not compulsory, students can drop out of school at age 16. At the end of the eleventh year of schooling, students receive high school diplomas. Students who would like to enroll in college must attend a one-year pre-university program (Grade 12). For both upper-secondary and pre-university, students select an academic stream in either humanities, mathematics&physics, or natural sciences. Pre-university students and graduates can register for the university entrance exam (known as Concour). Candidates register for the exam in February, the exam is held once a year in June.[13] In August, students receive their scores and university admission booklets, which contain detailed information of each education program (we refer to the combination of a major and a university as a program, e.g., computer science at the Sharif University) including capacity. Then, they apply for universities by submitting a list of at most 100 programs in an order of preference from most to least preferred. The central authority, the National Organization of Educational Testing (Sanjesh), applies a one-sided Gale Shapley algorithm (serial dictatorship) to assign applicants to each program, after reviewing the applicants' entrance exam scores, their preferences, and the number of available seats by the program. There is no program-specific admission cutoff. Each applicant's chance of being accepted into a program only depends on their exam scores compared to other applicants' and the rank in their submitted application. Each applicant is offered at most one admission to their highest rank program for which their exam score is above their rivals. Thus, admission cutoffs into different majors are unpredictable for the applicants.

There are three major Concour exams (humanities, natural sciences, and mathematics & physics) that cover different subjects taught in high school and pre-university programs. Applicants can write only one of these three exams.[14] Applicants have a limited number of university majors to choose from based on the exam they write, e.g., only applicants who write exam in mathematics & physics can apply for engineering fields, only applicants who write exam in natural sciences can apply for health fields, and only applicants who write exam in humanities can apply for philosophy.

[13]university entrace exams:All public universities and many private universities (e.g., Gheyre-Entefaee universities) use this exam for the admission purpose. The only exception was Islamic Azad University (IAU), the largest private university in Iran, that had its own entrance exam which were held a few days after the Concour. Since 2013 IAU uses the Concour as well.

[14]Most applicants choose one of these three exams based on their major in high-school and pre-university.

Retaking the exam in later years is permitted for those who fail the first time.[15] However, there is a restriction for male candidates due to compulsory military service (CMS). Men older than 19 years old must go for two-year military service.[16] Secondary and university students can postpone their military service for certain years. In particular, pre-university students are deferred until their graduation (maximum to 20 years old). Also, CMS recruitment date allows pre-university graduates to take the university exam before going for military service. The recruitment date depends on the birth date; recruitment year is calculated as 19 + birth year; recruitment months are November, December, January, and February for those who were born in Spring, Summer, Fall, and Winter, respectively. Therefore, boys can take the Concour at most twice before going for military service. Boys who were born in the first half of the year can write the exam twice, while boys who were born in the second half of the year can write the exam only once. For example, boys who were born in the first half of 1993 will be sent to military service in November/December 2012. These cohorts typically graduate from pre-university program in academic year 2010-2011 and thus can take university exams in June 2011 and June 2012.[17] Boys who were born in the second half of the year 1992 also graduate from pre-university program in academic year 2010-2011. However, since they will go to military service in January/February 2012, they are not allowed to take university exam in June 2012. While women are exempted from CMS and thus there is no such restriction for girls, writing the exam for the third time is rare among girls too. Figure E.2 shows the age distribution of 2012 applicants. As this Figure shows, 84% of applicants are 20 years old or younger (82% of female and 87% of male candidates). The average and median age is 19 years old, and there is no gender differences. In this year, 56% of female and 64% of male candidates write the exam for the first time (Source: Iranian University Applicants Data).

2.2 The 2012 Gender Quota in College Admissions

Despite the various barriers to women's education in Iran, female students still outperform their male counterparts on university entrance exams as well as in graduation rates. In 2011, 55% of the first-year university students, 52% of the university graduates, and 68% of the science degree graduates are women (Source: Institute for Research and Planning in Higher Education (IRPHE)). Table 1 reports the difference in university majors between female and male students in 2011. For example, while women were the minority in engineering and services (40%), they took 80% and 70% in education and humanities, respectively. In 2012, 57% of university applicants were female (Ekbatani, 2022). These trends raised concerns about social consequences, including declining marriage and fertility rates.

On August 20 2012, Iran's Ministry of Science, Research and Technology announced restrictions on public university entry for female students. The 2012 gender quota on higher education was surprisingly

[15] Those who get admission in a university program but do not enroll are not allowed to repeat the exam in the following year. The reason of such a policy is preventing applicants from randomly selecting programs that they do not like and occupying a spot that could have been filled by another applicants.

[16] They are called for military services in the years they will be 18 years old, but the recruitment age is 19. Men who refuse military service will not be able to apply for an academic program, job, driver's license, and passport.

[17] If they enroll in university in September 2012, they are allowed to defer military service until the end of their college education (maximum to 5 years).

announced on the date when university applicants received their results of the university entrance exam and were preparing to submit their preferred list of university programs. While most public university majors were affected by the quota, some were more affected than others. 36 public universities cut 77 programs from the female curriculum, making them male-only including programs in engineering (civil engineering, Electrical engineering, Marine Engineering, etc.), science (physics, statistics, chemistry, etc.), and social science (law, management, education, geography, etc.). Meanwhile, the quota sets the targeting proportion of female and male students in different programs. For example, based on the quota, 38% of seats in engineering programs are reserved for males and 17% for females. As a result, female enrollment in engineering programs drops significantly. Women comprise 38.8% of engineering students in 2011 (before the quota),[18] this share falls to 32% in 2012. In health and welfare programs, only 10% of seats are reserved (2% for males and 8% for females), and applicants can freely compete over the other 90% of seats. The variations in the quota intensity arise from differences in the concentration of gender-segregated workplaces and social norms. Some workplaces can easily practice gender-segregation, such as hospitals and schools. Therefore, while studying medical sciences, which are considered feminine majors, is socially accepted, social norms discourage women from entering masculine majors, such as engineering (Mehran, 2003).

Based on the policy documents, there are three reasons for imposing this policy: 1. the lack of employers' demand for female graduates of certain college majors (e.g. engineering)[19] 2. some majors are socially inappropriate for women (e.g., agriculture and mining) 3. a shortage of available female dormitories. Besides these official reasons, the Iranian government might tend to create more employment opportunities for highly educated men through the 2012 gender quota. The men's unemployment rate was 10.5% in 2011 (Source: Statistical Center of Iran). It is also believed that policymaker limited educational opportunities for women to increase the fertility rate. The fertility rate in Iran decreased from 6.5 in 1975-1980 to 1.9 in 2005-2010 (Source: The UN's Population Division of the Department of Economic and Social Affairs). The ageing and shrinking population raise concerns about the social costs and the labor shortage.[20] The quota continues for the years 2013 and (by a few universities in) 2014, and is lifted in 2015. Table I.5 (in Appendix I) shows that lifting quota in 2015 slightly reduce men's college enrollment, while there is no significant effect on women's. These effects are expected. Admission to the public universities is competitive and thus candidate have to plan and prepare for the

[18]This share is one of the highest in the world. In Canada, UK, and the United States, around 20% of students in undergraduate engineering students were women in 2011.

[19]In 2011, 38% and 25% of women with a bachelor's degree in engineering fields were non-participant and unemployed, respectively.

[20]The gender quota was supported widely by different political institutions. For example, the chair of the research center of Parliament supported this policy as an important way to balance the marriage market. He claimed that if there are more educated women in the marriage market, some of them have to either get married to an uneducated men or remain single, which threatens family structure. Also, many members of Parliament support this policy with an emphasize on the labor market conditions. For example, a member of Parliament mentioned the low labor mobility of female workers and concluded that social investment in women's human capital is not efficient. Many other supports were based on ideological reasons. They argue that since Islam assigns the role of supporting the family financially to men, an Islamic society should provide job opportunities for men. Thus, " every woman entering university and then the labor market is a factor in the unemployment of more men who, according to Islam, are the breadwinners of the family."

university entrance exam several years before taking the exam. Therefore, those girl students who did not get prepared for the university exam cannot be successful in this competition even after the quota is lifted.

The effect of the 2012 gender quota on college enrollment (and other lifetime outcomes) is not clear because affected female applicants who are prevented from choosing their preferred program can choose a different major or the same major in another university (in particular, they may enroll in a private university).[21] We empirically test the overall effect of this policy on education and labor market outcomes.

3 Data and Descriptive Evidence

3.1 Data

The main data used in this paper is from the 2005-2018 Iranian Labor Force Survey (ILFS), a nationally representative cross-sectional sample provided by the International Labour Organization (ILO) and the Statistical Centre of Iran.[22] The ILFS collects the data on 140,000-170,000 individuals quarterly using random sampling.[23] The ILFS is appropriate for studying the effects of gender quota because of three reasons. First, it provides detailed individual information on educational level and major. Thus, we can not only estimate the effect on college enrollment but also check the extensional impact on pre-university enrollment, high-school completion, and high-school drop-out. Second, it provides information on employment status and occupation that enables us to study the labor market impact, i.e., whether the labor market is restructured by new entrants and how the occupation is matched.[24] Third, it includes demographic information (e.g., birth year and month) and family characteristics (e.g., parents' education, family size, etc). In particular, observing the birth date allows us to exploit the discontinuity in outcome variables across birth cohorts.

We also use 2005-2018 Iranian Households Income and Expenditure Survey (HIES) for analyzing the effects on wages because ILFS data do not include any earning information.[25] There are 245,927 year-individual observations in the HIES data for our analysis on wage. We do not use the HIES data for the rest of the analysis because of its small sample size as the HIES comprises less than half of the observations in the ILFS data. Also, HIES is not as rich as ILFS in educational information and birth

[21] Public and private universities differ in terms of cost and quality of education. Public universities are of high quality and free tuition, thus these programs are highly competitive. Private universities charge tuition fees and typically place lower in the university rankings than public universities. Female students are less likely to enroll at a private university. 34% and 36% of female first-year college students (compared to 48% and 49% of male first-year college students) are in private universities in 2011 and 2012, respectively.

[22] Publicly available on www.amar.org.ir.

[23] The response rates in all rounds are at 81-89%.

[24] For those who are employed, we observe the industry according to the International Standard Industrial Classification (ISIC) and job title according to the International standard classification of occupation (ISCO). Also, unemployed individuals are asked about their idea job characteristics. This feature of data allows us to check changes in working preference.

[25] HIES is also publicly available on www.amar.org.ir

date, e.g., college major and month of birth are not observable in HIES. We use this data to predict worker wages in our main sample (details are provided in Appendix C).

The quota records are obtained from a list of PDF files of the university admission booklets that specify the number of seats in each university program in 2012.[26] The data provide information on how many seats are open to only male candidates, only to female candidates, and to both genders. Table D.1 presents translation of some parts of 2012 admission booklets. The quota information from admission booklets combined with the gender distribution of first-year students in 2011 can show the magnitude of the quota. For example in 2011, women made up 39% of first-year students in engineering at the Shahid Chamran University (Source: Institute for Research and Planning in Higher Education). The 2012 gender quota made all engineering majors at this university male-only. As another example, the quota divided seats in sciences (Statistics, Mathematics, Physics, and Chemistry) equally between female and male students at Isfahan University of Technology, despite the fact that women made up 60% of first-year science students at this university in 2011 (Source: Institute for Research and Planning in Higher Education). Table 1 summarizes 2012 quotas and 2011 first-year students information across group of college majors. We use this data to calculate treatment intensity across provinces and estimate the distributional impacts of the quota in the section 7.

4 Empirical Strategy

Different cohorts of students would have been exposed to different economic trends, which might have influenced their decisions over education and career. Thus, we use a regression discontinuity (RD) design to solve this problem by comparing the educational attainment and employment status of people born close together. Iranian education system offers an exogenous variation across the birth cohort, allowing us to apply a sharp RD method. Due to age restrictions for enrolling and completing each grade in the Iranian education system, students from the same birth cohort graduate from pre-university program at the same academic year. Our sample comprises those who were born just before and after the cutoff points. University applicants for the 2012 university entrance exam are those who write the exam for the first time (were born between September 1993 - August 1994) and those who write the exam for the second time (were born between September 1992 - August 1993).[27] Thus, we use the birth cohort of September 1992 as the cutoff for college enrollment. These students are comparable because they experience almost the same economic development while growing up. The key difference is that those born just after September 1992 would have been affected by the education quota, especially for the female who may not continue their school as being restricted. Their counterparts are the people born before September 1992, who are not restricted by the new quota. Using the RD approach, the causal

[26] PDF files are publicly available on www.sanjesh.org and academics.ut.ac.ir.

[27] We assume people do not write the exam more than twice. This assumption is reasonable and supported by direct evidence. As explained before, male candidates are not allowed to take the exam as soon as they they become eligible for compulsory military service. Although there is no such restriction for girls, exam demographic statistics indicate that girls rarely write the exam more than twice.

effect of the education quota can be estimated by a regression model as follows:

$$Y_i = \alpha + \rho D_i + \beta_1 f(\widetilde{x}_i) + \beta_2 D_i f(\widetilde{x}_i) + X_i^T \mathbf{B} + \epsilon_i \tag{1}$$

where Y_i is the outcome variable of individual i (education and labor market outcomes). The 2012 education quota generates a cutoff with respect to an individual's birth month. The variable D_i is the treatment indicator, which takes the value one if the person is born after September 1992, zero otherwise. $\widetilde{x}_i$ indicates the number of months away from the cutoff for person i. It takes negative value if the individual's birth month is to the left of the cutoff. The main specification uses a bandwidth of 12 months, but larger bandwidths are also estimated. $f()$ is an unknown function used to capture the flexible trend in $\widetilde{x}_i$ around the threshold. We adopt a linear regression approach to estimate the causal effect. For sensitivity check, we also estimate the regression using a linear or quadratic form of $f()$. The interaction term $D_i f(\widetilde{x}_i)$ allows different trends across the cutoff. X_i^T is a vector of individual characteristics, including dummy for age, province, and urban area. These regressors control for variations in sample composition. The error term ϵ_i captures all the other factors that affect the outcome variables. For college enrollment, our sample consists of individuals who graduated from high school around the time of the quota enforcement. For labor market outcomes, we limit this sample to those individuals who graduated from high school but did not go to college. The coefficient ρ is the RD estimate of our primary interest because it captures the local average treatment effect on the treated of the 2012 education quota.

Identification Assumptions. In this section, we present standard tests of the validity of our RD design. The validity of our estimation methods requires several identification assumptions. First, individuals' birth month should not be manipulated by their parents in anticipation of the policy change. Manipulation of the birth date is highly implausible, especially because parents did not know that there would be an education policy in 2012. Still, to check for any signs of manipulation, we test for a discontinuity in the density of the birth date around the cutoff (Figure E.1) and we find no visible sign of such a discontinuity. Also, we use a test suggested by Frandsen (2017), the test fails to reject the null hypothesis of no manipulation.[28]

Second, we investigate whether there are any discontinuities in other variables that potentially impact outcomes at the cutoff, which violate the exclusion restriction. We focus on a set of socioeconomic variables, including parents' education, parents' work status, family size, and number of siblings. Figure E.3 shows that covariates change smoothly around the cutoff. Also, using a set of balance checks, we find no evidence of a substantial change in these factors near the cutoff, supporting the fundamental supposition that the 2012 education quota was the only systematic trend shift that had an impact on educational results across cohorts.

We estimate the effects with an MSE-optimal bandwidth h=24 months (24 months before and 24 months after the cutoff) and a linear spline model. In Section 6, we conduct several robustness checks (different bandwidths and different specifications for the smooth function) to check the sensitivity of

[28]Manipulations test: pvalue=0.503 (k=0.02), pvalue=0.234 (k=0.01), pvalue=0.144 (k=0.0).

our results.

5 Estimation Results

We analyze the direct impact of the 2012 education quota on education outcomes and the indirect effects on labor market outcomes.

5.1 Effect on Education Outcomes

We first examine the quota effects on education outcomes including college attendance, pre-university attendance and major decision, and high school completion.[29]

Figure 1 shows how the college enrollment rate varies with age cohorts around the threshold. While women's college enrollment rate suddenly dropped from 54% to 51% (a 5.5% decrease) in the year of the quota implementation, there was no change in men's college enrollment. Table 2 presents the estimated effects on college enrollment. For this analysis, we restrict our sample to high-school graduates. The estimated results show a sharp decline in women's college attendance rate at the cutoff by 2.5 percentage points and an insignificant increase in men's college attendance. These results are robust to several choices made in the analysis including different model specifications (with and without control variables). The aggregate data of the student population show a similar pattern. Overall, the population of first-year female students (2/4-year programs and medical schools) decreases from 496,736 in 2011 to 436,236 in 2012, while the population of first-year male students increases from 524,264 in 2011 to 556,976 in 2012. The effects are different in public and private universities. This policy affected only public universities, thus female applicants may shift to private universities. However, private universities are expensive and offer relatively lower-quality education. Although we cannot formally investigate different effects on public/private university enrollment (because we do not observe the type of universities in the data), the aggregate data show evidence of changes in student gender distribution in public and private universities. The aggregate data show that the population of female first-year students in public universities decreases from 318,249 in 2011 to 264,760 in 2012, while the population of male first-year students increases from 277,178 in 2011 to 288,778 in 2012. On the contrary, the share of female students increases in private universities. In particular, the population of female students in 4-year programs and medical schools at the Islamic Azad University, which is the main private university system in Iran, increases from 35,822 in 2011 to 75,759 in 2012 (female share increases from 24% in 2011 to 43% in 2012) (source: aggregate college students data reported by the Ministry of Science, Research, and Technology).[30]

Although there is no difference in the rate and timing of high school graduation between treatment

[29] In Iran, education is compulsory up to the 9th grade, thus we expect that the quota to affect enrollment in high school and/or higher education, if there is any effect.

[30] Therefore, the policy makes a change in both quantity and quality of women's education. Affected women who go to private universities may have bleak career prospects. Investigating the effect of this policy on educated workers is left for future work.

and control groups,[31], the quota may affect high school education of students who reach high school drop out age after the quota. The effects on women's secondary education is ambiguous. On the one hand, fewer post-secondary educational opportunities may discourage marginal female students from completing high school and attending a pre-university program. On the other hand, inflow of high-skilled women who are prevented from entering college by the quota to the pool of female HSGs increases the average productivity of this group of workers. This change increases the signaling return to graduating from high school that makes an incentive to complete high school and hide behind being constrained. (Bedard, 2001). We empirically test the overall impact. Table 3 presents the effects on enrollment in pre-university program and high school. While there is no significant effect on boys' pre-university attendance rate, girls' enrollment decreased by 2 pp from 89% (2%). Although the effect on the girls' pre-university enrollment is small, it can have long-lasting effects. Due to the age restrictions for school entry and completion, the marginal girls who did not enter the pre-university program are not allowed to return to school, obtain a pre-university degree, and apply for college programs once the quotas are lifted.[32] Although the quota has no significant effect on completing high school, the probability of dropping out from high school decreases by 2-3 pp for boys from 6% (33%). Changes in college and pre-university enrollment have economic and social impacts. In the next section, we investigate the quota effects on labor market outcomes.

5.2 Effect on Labor Market Outcomes

The quota can have indirect effects through the channel of education changes. Girls growing up through the period of quota implementation, experiencing fewer educational opportunities may have different lifetime outcomes. In this section, we present the effects on the labor market outcomes (employment and wage rates) of the treated group. We also examine how changes in the relative supply of young high-school graduates affect the overall employment and wage structure (elasticities and gender wage gap).

5.2.1 Effect on Employment and Wage Rates

Table 4 presents the effects on employment status and wage rates among HS graduates. We use the sample of young individuals (age<28) with a high school/pre-university degree who were born after September 1992 as the treated group and those who were born before September 1992 as the control group. Since entering the treated group in the labor market can affect labor market outcomes of the control group, we restrict observations of the control group to years before 2012 and observations of the treated group to years after 2012, though our results are robust to the sample selection. As Table 4 shows,

[31] Because the policy was unexpectedly announced and implemented in August when both cohorts had already graduated from high school

[32] There are age restrictions for enrollment at each grade. Detail information is available on the website of the Ministry of Education (in Persian). The maximum age eligible for completing high school and enrolling in a pre-university program is 20 and 21, respectively. Older people can enroll in the adult education system which is not available in all cities due to low demand. We find no significant change in enrollment in the adult education system.

compared to control women, the treated female cohort has a significantly higher LFP and employment rates and lower unemployment rates, while there is no significant effect on men's labor market outcomes. Treated women who are restricted by the quota from attending college are more likely to participate in the labor market and have a job by 3 pp compared to control HSG women. Also, as Panel C shows, there is no significant effect on overall labor market outcomes; only the gender composition changed. This finding is not surprising given that women accounted for a relatively small fraction of the Iranian labor force. Women account for 17% of all young HSG labor force participants.

Changes in the relative supply of young HSG women and skill structure of labor force can affect the wage rates. On the one hand, the increase in the relative supply of HSG workers may decrease their wage rates. On the other hand, there is a variation of skills between different cohorts and genders, in particular, young women may be more productive than their male and older female counterparts and hence be paid higher wage rates. As Table 4 shows, while the wage rate of treated female HSG significantly increases (by 0.6% compared to control female HSG), there is no effect on man's wage rate. Since the change in the gender wage gap for different cohorts can be related to different age and year effects, we decompose wage changes into cohort, age, and time effects (Table F.1 in Appendix F) and find evidence for the cohort effect in the reduction in wage gender gap among young HSG cohorts. Comparing average earnings of college and high-school graduated workers across cohorts shows a 20% reduction in college wage premium among treated female workers which is in line with the literature of the signaling effect of attending college. Compliers are not able to use a college degree as a signal of their unobserved skills and employers know it. Current empirical studies that distinguish human capital returns from signaling returns to schooling find sizable effect of signaling. In particular, Aryal et al. (2022) find that 30% of returns to education is the signaling effect. Furthermore, using the conventional method of taking the ratio of the change in log wages (0.6%) and the change in labor supply (2.7%), gives us a change of about (0.6/2.7=) 22% which lies within the range of comparable estimates found in the literature of the effects of labor supply shocks on the wage rates. A large body of empirical studies use immigration changes as an exogenous shock in labor supply and estimate spillover effects on the wage rates of workers whose skills are similar to those of new immigrants. The estimated results of a one percent increase in supply vary widely depending on how immigrant inflows affect skills distribution. For example, while Card (2009) and Dustmann et al. (2017) find that a one percentage point increase in labor supply has almost no effect and a moderate negative effect (-0.13%) on native wages, Borjas (2003) find a negative effect (-0.4%) and Ottaviano and Peri (2012) find a positive effect (between 0.6% and 1.7%). There are at least two explanations for such contradictory results in the empirical literature. First, wages are downward rigid, at least in the short run and for high-skilled workers who are more likely to be covered by long-term contracts than low-skilled workers (Card et al., 1999; Dustmann et al., 2017). Second, immigrants and natives with the same skill set are imperfect substitutes, thus increases in immigrant inflows mostly affect immigrants themselves and have a relatively small impact on natives (Card, 2009; Dustmann et al., 2016).

5.2.2 Effect on Occupational Choices

There are at least two potential explanations for the reduction in the gender wage gap among HSG workers: treated women receive higher wages than their counterparts in the same occupation and/or treated women may enter into higher-paying jobs. We provide evidence of within and between occupation differences in the wage rates.[33]

We first investigate changes in the gender wage gap within occupations. One hypothesis to explain the increase in the relative supply of female HSG workers and reduction in wage gender gap is that relative demand for young female HSG workers increases faster than relative supply. As a result of the quota, male students enrolled in college need not be the most qualified and may displace qualified women. The qualified women who were prevented from continuing their education (defiers) may not be perfect substitutes for either other high-school graduates who graduated before this policy or high-school men graduates in the same birth cohort. Employers may offer higher wages to this group of women to attract them. To examine this hypothesis, we control for occupation dummies and estimate the coefficient on women's wage rate (model (4) of Table 4). Absorbing the effect of occupation decreases the coefficient by 30% for female workers (model (3) and (4)), indicating the intra-occupational wage differential is more important than the inter-occupational wage differential. Thus, young HSG women are offered higher wage rates than their old female counterparts, such that their wage rate become more close to their male coworkers.

We also investigate the effect of the education quota on occupational choices of affected women. Table G.1 presents descriptive statistics for employed female HSG workers. This table shows four facts. First, as Panel A shows, most female HSG workers are either employees in the private sector (36%), self-employed (28%), or unpaid family workers (24%). Second, as Panel B shows, manufacturing (42%), agriculture (20%), and retail (11%) provide major sources of employment opportunities for female HSG workers, followed by other service activities, education, and health. Third, as Panel C shows, occupations with larger employment size are manual and services; of female workers, 75% work in craft, service, and skilled agricultural occupations. Fourth, there are significant differences between control and treated women in employment in different occupations. In particular, treated women are more likely to be self-employed (in other service activities) and less likely to be unpaid family workers (in agriculture sector). Also, treated women are more likely to get middle-skilled jobs in the private sector than control women. Figure 3 (and Table G.3) presents the estimated effects on the occupations of female HSG workers. As Figure 3(a) shows, the probability of being self-employed and employed in the private sector increases by 2.1 and 1.0 percentage points, respectively. The shift from unpaid family jobs to

[33] Another possible explanation is related to technological changes. As Acemoglu and Autor (2011) show, in the US, low-skilled, particularly low-skilled male workers experienced reduction in earnings due to technological developments. Thus, if there is no or smaller effect on female workers, the gender wage gap will decrease. Such an explanation is important in our case because as Dustmann and Glitz (2015) shows, firms change their production technology in response to changes in skill distribution of the labor force. Although we cannot test this hypothesis formally, technological advancements are unlikely to be source of wage changes across cohorts in Iran because the real wages of college graduated high-skilled workers have been declining over the years of this study. In fact, nominal wage rates increased, but had not been synchronized with the rate of inflation.

paid-jobs explains some increases in women's wages. Moreover, the earnings of self-employed workers are relatively high, though the largest variation is observed in earnings of this group of workers.[34] Also, women's employment increases in relatively higher-paying occupations. As Figures 3(b) and 3(c) show, affected women's employment increases in manufacturing, professional, and other services industries as service workers and technicians. As Table G.4 shows, the wage rates of these occupations are relatively high.

It is important to mention that such changes in women's occupations are determined by the interaction between supply and demand factors: treated young women's preferences may lead them to choose different occupations than older women and/or employers are more likely to hire these young women in certain occupations. On the supply side, a rich literature following Polachek (1981) provides evidence of significant gender differences in occupational self-selection due to differences in their attitudes toward risk, competition, and skills requirement in different workplaces. On the demand side, another influential literature documents employers' discriminatory behaviours (taste-based and statistical discrimination) that result in different treatment between men and women despite having equal abilities and preferences (Black and Strahan, 2001; Goldin and Rouse, 2000). Information frictions in the labor market cause statistical discrimination. In particular, since workers' productivity is not fully observable, employers make hiring decisions based on the average productivity of different (education/race/gender) groups. Observing the performance of their previous employees and interacting with different groups of workers affect how employers form beliefs about the average productivity of different workers (**?**). Employers update their beliefs by receiving new information about the productivity of workers. The 2012 education quota provides a new set of information regarding the productivity of young women and men who did not enter college. Empirically, it is difficult to distinguish between workers' preferences and employers' discrimination, especially because of their integrative effects: labor market conditions affect work preferences and workers' preferences affect employers' beliefs. Here, we discuss evidence of no changes in the working preferences of women. In our data, unemployed individuals are asked about their preferences over working hours, being employed or self-employed, and working sector (agricultural, industry, services). We find no significant effect on unemployed women's working preferences (Table G.5), though these results cannot be generalized to the whole population as working preferences of employed individuals are not observable in our data.

5.2.3 Elasticities of Substitution

The entry of these young women into the labor market and new occupations may have an effect on other HSG workers. As explained in section 5.2.2, affected women were successful in getting relatively higher-paying jobs as service workers and technicians in manufacturing and professional industries. These occupations have traditionally been occupied by men and experienced older women. Young women may potentially push out young males, older males, and older females. It is interesting to ask for whom

[34] On average, public sector jobs pay the most, but there are not much opportunities for low skilled workers in the public sector. More than 80% of jobs in the public sector require a college degree.

young female workers substitute for. We calculate elasticities of substitution between women and men and between young and older cohorts. Existing research examine the effects of returning to school under the presumption that people of different sexes and birth cohorts with the same level of education make perfect substitutes in the workforce. In this section, we develop a model based on Card and Lemieux (2001). Card and Lemieux (2001) use the nested CES model with skill and age as dimensions of heterogeneity, and estimate elasticities of substitution between high-school and college graduates and between workers with the same education in different age groups. We add to their model in two ways. First, we allow imperfect substitution between men and women from the same birth cohort with the same education level (gender heterogeneity). Second, to address endogeneity concerns about wages and employment, we use the 2012 education quota as a source of exogenous variation in the labor supply.

We assume that aggregate output in jobs for high school graduates at time t, y_t, depends on two CES subaggregates of female and male labor (L_t^f and L_t^m), and the technological efficiency (θ_t).[35] Following the existing literature, we assume that the aggregate production function is also CES:

$$y_t = f(L_t^f, L_t^m; \theta_t) = [\theta_t^f (L_t^f)^\rho + \theta_t^m (L_t^m)^\rho]^{1/\rho} \tag{2}$$

in which

$$L_t^f = \left[\sum \alpha_c (L_{ct}^f)^\eta\right]^{1/\eta} \tag{3}$$

$$L_t^m = \left[\sum \beta_c (L_{ct}^m)^\eta\right]^{1/\eta} \tag{4}$$

where L_{ct}^f and L_{ct}^m are female and male labor of cohort c at time t. $-\infty < \eta \leq 1$ is a function of the partial elasticity of substitution between different cohort groups, σ_C ($\eta = 1 - 1/\sigma_C$).[36] $-\infty < \rho \leq 1$ is a function of the partial elasticity of substitution between women and men, σ_S ($\rho = 1 - 1/\sigma_S$). α_c and β_c are relative efficiency parameters of female and male workers cohort c, respectively. We assume efficiency parameters are fixed over time.

Firms' demand for different labors is determined where relative wages are equated to relative marginal products (for more detail see the online Appendix):

$$\log\left(\frac{w_{ct}^f}{w_{ct}^m}\right) = \log\left(\frac{\theta_t^f}{\theta_t^m}\right) + (\rho-\eta) log\left(\frac{L_t^f}{L_t^m}\right) + \log\left(\frac{\alpha_c}{\beta_c}\right) + (\eta-1) log\left(\frac{L_{ct}^f}{L_{ct}^m}\right)$$

Thus, wage gap of women and men workers in the cohort group c in the year t is:

$$\Rightarrow \log\left(\frac{w_{ct}^f}{w_{ct}^m}\right) = \log\left(\frac{\theta_t^f}{\theta_t^m}\right) + \log\left(\frac{\alpha_c}{\beta_c}\right) + \left[\frac{1}{\sigma_C} - \frac{1}{\sigma_S}\right] log\left(\frac{L_t^f}{L_t^m}\right) - \left(\frac{1}{\sigma_C}\right) log\left(\frac{L_{ct}^f}{L_{ct}^m}\right) + e_{ct} \tag{5}$$

[35] Iran's labor market is strictly segregated according to education. Most positions require candidates to have a certain level of education. High school graduates are not qualified for jobs that require a college degree. Also, college graduates are not allowed to apply for jobs that require a high-school diploma.

[36] Under perfect substitution assumption in Card and Lemieux (2001), η is equal to 1 and total women (or men) labor input is just a weighted sum of the quantity of labor supplied by each cohort group.

According to this model, the gender gap for a given cohort group depends on both labor quality and quantity. An increase in cohort-specific relative productivity of women, $\log\left(\frac{\alpha_c}{\beta_c}\right)$, increases female relative wages. Also, the cohort-specific gender gap depends on the labor quantity: both the aggregate relative supply of female labor $\left(\frac{L_t^f}{L_t^m}\right)$ in period t, and on the cohort-specific relative supply of female labor $\left(\frac{L_{ct}^f}{L_{ct}^m}\right)$. Any change in cohort-specific relative supplies would be expected to shift the cohort profile of the gender wage gap, with an effect that depends on the size of $1/\sigma_C$.[37] The effect of the aggregate relative supply of female labor depends on the magnitude of σ_C and σ_S. If $\sigma_S > \sigma_C > 0$, an increase in the aggregate relative supply of female labor increases female relative wages. e_{ct} reflects sampling variation in the measured gap or any other sources of variation in cohort-specific wage gap.

Empirical Strategy and Estimation Results. We estimate the effects of the change in the relative supply of women workers on the gender wage gap in three steps. The major challenge of estimating the elasticities is the endogeneity of labor supply. The market-clearing condition assumption (and thus an inelastic labor supply) in Card and Lemieux (2001), which is reasonable for the US, cannot be true in the case of Iran.[38] In the first step, to address endogeneity concerns, we instrument cohort-specific and aggregate relative supply indexes with the interaction effect of being treated cohort after the education policy imposed in 2012 using an RDD analysis:

$$\log\left(\frac{L_{ct}^f}{L_{ct}^m}\right) = \nu + \rho D_{ct} + \gamma_1 f(\widetilde{x}_{ct}) + \gamma_2 D_{ct} f(\widetilde{x}_{ct}) + \varepsilon_{ct} \tag{6}$$

and

$$\log\left(\frac{L_t^f}{L_t^m}\right) = \nu^{'} + \rho^{'} D_t + \gamma_1^{'} g(\widetilde{x}_t) + \gamma_2^{'} D_t g(\widetilde{x}_t) + \varepsilon_t \tag{7}$$

where D_{ct} is the treated cohort dummy (born after September 1992) and $\widetilde{x}_{ct}$ indicates the number of months away from the birth cutoff (September 1992) for cohort c at observed at time t. Similarly, D_t is the treatment time dummy ($t \geq 2012$), and $\widetilde{x}_t$ indicates the distance of time from the time cutoff (September 2012). $f()$ and $g()$ are smooth functions that capture the trend around the threshold. The parameters ρ and $\rho^{'}$ measure the local average treatment effect of the education quota on the cohort-specific and aggregate relative supply indexes, respectively.

In the second step, we estimate σ_C from a regression of the cohort-specific gender income gap on cohort-specific relative supplies of HSG labor, cohort effects, and time effects. Eq (5) can be written as follows:

$$\log\left(\frac{w_{ct}^f}{w_{ct}^m}\right) = -\frac{1}{\sigma_C}\log\left(\frac{L_{ct}^f}{L_{ct}^m}\right) + \phi_c + \lambda_t + e_{ct} \tag{8}$$

where ϕ_c and λ_t are cohort and year effects, respectively. λ_t absorbs the relative productivity shock over time, $\log\left(\frac{\theta_t^f}{\theta_t^m}\right)$, and any effect of aggregate relative supply, $log\left(\frac{L_t^f}{L_t^m}\right)$. Also, ϕ_c absorbs any changes in

[37] if $\sigma_C > 0$, cohort-specific relative supply of female labor has a negative effect on female relative wages.

[38] Fitzenberger and Kohn (2006) also argue that this assumption is controversial in the case of Germany, as it neglects the unemployment. They use an IV approach and instrument employment by labor force to solve the endegoneity problem.

cohort-specific relative productivity of women, $\log\left(\frac{\alpha_c}{\beta_c}\right)$. We use fitted value of cohort-specific relative supply index, $\log\left(\frac{L^f_{ct}}{L^m_{ct}}\right)$, derived from the first step, Eq (6), into Eq (8).

The third step is to estimate the elasticity of substitution between men and women σ_S. Eq (5) can be written as follows:

$$\log\left(\frac{w^f_{ct}}{w^m_{ct}}\right) = \log\left(\frac{\theta^f_t}{\theta^m_t}\right) + \log\left(\frac{\alpha_c}{\beta_c}\right) - \frac{1}{\sigma_S} log\left(\frac{L^f_t}{L^m_t}\right) - \frac{1}{\sigma_C}\left[\log\left(\frac{L^f_{ct}}{L^m_{ct}}\right) - \log\left(\frac{L^f_t}{L^m_t}\right)\right] + e_{ct} \tag{9}$$

which include both the aggregate relative supply index, $\log\left(\frac{L^f_t}{L^m_t}\right)$, and the deviation between the cohort-specific relative supply of female workers and the aggregate supply index, $\log\left(\frac{L^f_{ct}}{L^m_{ct}}\right) - \log\left(\frac{L^f_t}{L^m_t}\right)$. We use fitted values of cohort-specific relative supply index and the aggregate supply index derived from the first step (Eq 6 and Eq 7).

Table 5 presents the estimation results. As the estimation of the first step (Panel B) shows, the education quota increased the cohort-specific and aggregate relative supply of female HSG workers such that the decreasing trend of the relative supply of female HSG workers significantly turned to an increasing trend among affected cohorts and after 2012. The F-statistic in the corresponding first step regressions is far above the critical value, indicating that the used instruments are relevant.

Estimates of the second and third steps reveal two main findings. First, we find that the entering of high productive young women push older women out of the labor market. The first column of Panel A shows the regression results of the gender income gap on the cohort-specific relative supply, birth cohort, and year effects (Eq 8). The results implies an elasticity of substitution between different cohort groups of 10.2 ($\sigma_C = -\dfrac{1}{-0.098}$), suggesting that young and older female cohorts are substitute in the production process. In particular, young treated women take jobs away from older female workers. While traditionally, female HSG workers would need work experience to get well-paying middle-skill jobs, young treated women were able to get these positions without any experience.[39] Second, we find female and male workers are complements in the workplace. Estimates of the third step (Panel A, two last columns, Eq 9) implies an elasticity of substitution between different gender groups of -2.8 ($\sigma_S = -\dfrac{1}{0.352}$).

One possible explanation for these findings is occupational segregation by gender. If there is such segregation, it would be hard to substitute treated women for men in male occupations. As Table G.2 shows the overall share of women has increased especially in manual and services work which provides the major source of employment opportunities for high school graduates. Yet, all occupations but professionals remain predominantly male. To check whether entering young cohorts of women into different occupations reduce labor market discrimination, we measure occupational segregation before

[39]The estimates of σ_C from the third stage is the same as the second step estimates.

and after imposing the quotas. We use the segregation index developed by Duncan and Duncan (1955):

$$S = 0.5 \sum_j |M_j - F_j| \tag{10}$$

where M_j and F_j are the fraction of all employed HSG males and females who work in occupation j, respectively. The segregation index is zero if share of women in all occupations is the same as their share of total employment; and it equals one if all occupations are either completely male or completely female. According to Massey and Denton (2019), low segregation is defined as an index of segregation of 0.3 or less; moderate segregation is defined as 0.4 to 0.6; and high segregation is defined as above 0.6. Our calculation shows that occupations are moderately gender segregated among HSG workers (around 0.5), which is comparable to that of western countries (Blau et al., 2013). We also find while there has been increasing gender segregation across occupations over years before 2012, the degree of occupational segregation declines by 3 pp (from 0.55 to 0.52) in 2012 and remains relatively stable. Despite such a reduction, occupations are still gender segregated. Both demand and supply sides of the market and its interactive effects account for this gender segregation: employers prefer gender balance in the workplace, and/or women do not apply for specific positions. Also, changes in the occupational gender distribution take a longer time. As previous studies show, once employers start hiring women in traditionally male occupations, women are more likely to apply for such occupations.

Our findings are in line with the literature documenting heterogeneity in elasticity of substitution across cohorts and occupations (Card and Lemieux, 2001; Bhalotra et al., 2018; Khanna, 2022), though current studies find male and female workers are substitute in the US labor market (Acemoglu et al., 2004; Johnson and Keane, 2013). In particular, they find that substitution between male and female labor is lower in manual and routine task-intensive occupations. Our findings complements these papers by studying the labor market of a developing country in which gender differences are stronger.

6 Robustness Check

In this section, we provide several robustness checks for our main results (Appendix I provides more details). First, we examine the sensitivity of our results to different bandwidths. The main results are estimated with h=24 months around the cutoff, which is an MSE-optimal bandwidth. We use smaller bandwidths ($12 \leq h < 24$) and obtain similar results with slightly larger standard errors (Figure I.1 and Figure I.2. Also, Table I.1 presents more details for h=12 months). Second, we check sensitivity to model specifications by comparing the results with and without control variables and find similar results (model (1) in Tables 2, 3, and 4). Third, following Imbens and Lemieux (2008), we re-conduct the analysis using different specifications for the smooth functions, $f(r_{ct})$ and $g(r_t)$, (including standard linear, quadratic, cubic functions, and allow for different slopes of the regression function on both sides of the cutoff). Overall, these sensitivity tests verify the robustness of the original results (Table I.2, and Table I.3). Finally, we conduct placebo tests by using the pre-reform data to examine effects at placebo cutoff values (fake policy years 2005-2011), and we find no significant effects (Figure I.3 and Table I.4).

One important concern is that endogenous migration could bias the results. In particular, affected women may migrate to continue their education. To explore this possibility, we estimate the effect of the education quota on migration patterns. Table I.6 shows that female students' migration within and across provinces is not changed significantly. Also, the quotas have no effects on female immigration to other countries.

The estimated effects are solely due to the education quota, if there is no particular systematic trend change that affected education and labor market outcomes across cohorts. We check two events that affected the treated and control groups differently. First, the UN economic sanctions (2006-2015) are likely to affect labor market conditions and so incentives for investment in education. These changes affected the Iranian economy much earlier and are likely to affect both control and treated cohorts similarly. Moreover, as Moeeni (2022) shows, the effect of the sanctions on educational outcomes are not different across gender.

7 Heterogeneous Effects

In this section, we re-conduct the analysis across demographic groups to investigate the distributional impacts of the quota. The distance between hometown and university is an important determinant of education program choice for Iranian students. The average distance Iranian students travel between hometown and university is 176 km (the median is 63 km) (Ekbatani, 2022). While staying in the home province is preferred for both male and female applicants, there are gender differences in migration propensities and distance moved for higher education.[40] Around 0.2% of university students study in an out-of-province university, among them only 20% are female. While candidates can freely apply to any universities, there are at least two barriers for moving out of province for college. One major obstacle is location-based quota that is implemented by the Supreme Council of the Cultural Revolution (Resolution No 507 in Persian) in August 1990. Based on a location-based quota system, all majors are classified into four groups: 1. in-province majors (which are available in most provinces; about 23% of majors); 2. in-region majors (which are not available in every province but are available in groups of neighboring provinces; 20% of majors); 3. in-territory majors (which are not available in every region but are available in groups of neighboring regions; 7% of majors); 4. in-country majors (which are available in some universities, about 50% of majors). While in-country majors are open to all applicants; 80% seats of in-province (in-region/in-territory) majors are reserved for in-province (in-region/in-territory) applicants (source: university admission booklets).[41] Applicant's location is defined based upon the

[40](Ekbatani, 2022) using a choice model and applicants' major choice data shows that while both female and male applicants are more likely to apply for universities that are located in their hometown, closer universities are more important to female candidates.

[41]There are a few majors in which 60% of seats are reserved for applicants from related location. These majors are considered as popular majors and include Electrical Engineering, Mechanical Engineering, Computer Engineering, Civil Engineering, Architectural Engineering, Industrial Engineering (for math& physics applicants); Medicine, Dentistry, Pharmacy, Veterinary Medicine (for natural sciences applicants); Law, Psychology, and Accounting (for humanities applicants).

province of their last three years of schooling (two years of high school and pre-university program). If the place of completing the last three years of schooling is not the same province, the province of birth is considered as their location. For international candidates, Tehran Province, which includes the capital Tehran is considered as their location. All 31 provinces are classified into nine regions and five territories. The second obstacle to attending college out of province is cultural considerations and credit constraints.

Since the intensity of the quota varies across provinces, we examine whether treated female HSGs whose location of residence were more exposed to the quotas have different labor market outcomes. We measure the treatment intensity of the quota by the percentage difference between the pre-treatment (in 2011) and the target (in 2012) share of female students in the college.

$$intensity_l = \frac{\text{share of female students in 2011} - \text{targeted share of female students in 2012}}{\text{share of female students in 2011}} \tag{11}$$

where l is the location (province/region/territory). We calculate the intensity for each province, region, and territory. Figure J.1 and Table J.1 show the intensity of the quota across provinces/regions/territories. Tehran Province, which includes the capital Tehran and many top universities, is among the most affected provinces by experiencing 14.1% reduction in the proportion of female students in the college (from 54.1% in 2011 to 46.5% in 2012). Also, the region one, which includes central provinces (Tehran, Zanjan, Semnan, Qazvin, Qom, Markazi, and Alborz provinces), and territory one, which includes central (region one) and northern provinces (region nine: Golestan, Gilan, and Mazandaran), experience the second high incident by 11.2% and 10.9% reduction, respectively. Table J.2 (Panle A-C) shows heterogeneous effects on women's employment and wage rates by location intensity. A one-percentage-point decrease in the proportion of female college students results in a 0.1-0.3 percentage point increase in women's labor force participation and employment propensity, and a 0.5-0.6 percentage point reduction in their unemployment rates. Also women's wage rates increases by 0.3-0.5%. The effects at province/regional/territory levels are not significantly different providing evidence of no change in inter-province movement. The data also show no change in migration pattern.

This finding is consistent with Ekbatani (2022) that shows 35% of 2012 applicants selected a program in their hometown as their first choice; 26% of their other choices were in the same city as their residence. Also, the first choice of applicants is located within on average 214 km of their home (with a standard deviation of 319 km). Affected women did not move to other provinces to go to college because of the cultural factors, credit constraints, or a low chance of getting admission in any university of other provinces due to location-based quotas.

8 Conclusion

In this paper, we investigate the effect of unobserved skills on labor market outcomes. Recent evidence has indicated the importance of different skills, however, the causal implications are limited because some skills remain unobservable. This paper seeks to fill the gap by examining the effects of unobserved skills using an exogenous shock in the skills distribution. The 2012 gender quota in Iran limited number of female students in many college majors, which reduces educational opportunities for young women who were graduated from high school after 2012. This policy affects both the size and skill distribution of high school graduates by selecting different individuals into college. We exploits the discontinuity in college enrollment across birth cohorts among high school graduates.

Relying on a regression discontinuity (RD) design and exploiting the discontinuity in college enrollment across birth cohorts, we find that the quotas decreased women's college attendance rate by 2.5 percentage points. Also, women were less likely to attend the pre-university program by 2 percentage points after the quotas. Young women who were not admitted but would have been in the absence of the quotas (compliers) may have different skills than their male and older counterparts. We examine the labor market outcomes of high school graduates who never attended college. We find that the affected high-school graduate women were more likely to participate in the labor market and having a job by 3 percentage points.

We find that labor market outcomes of high school workers depend on both the aggregate relative labor supply (quantity) and the age-group specific relative labor supply (quality). In particular, this change in size and characteristics of labor supply reduced the gender wage gap among high-school graduate workers. We find that both within and between occupation changes caused such a reduction in the gender wage gap. Treated young women were offered higher wage rates than their old female counterparts in the same occupation, such that their wage rate became closer to their male coworkers. Also, treated women entered into relatively higher-paying jobs in manufacturing, professional, and other services industries as service workers and technicians. Since these positions have traditionally been occupied by men and experienced older women, we estimate the elasticity of substitution between different birth and gender groups to find whom these young women substitute for in the labor market. Our estimates suggest that entering high productive young women pushed older women out of the labor market ($\sigma_C = 10.2$). Also, we find that female and male workers are complements in the production process ($\sigma_S = -2.8$) which can reflect the importance of gender-balance in the workplace for employers. The results of this paper highlight the role of information on hard-to-observe skills of workers such as standard tests that can decrease statistical discrimination.

This study makes several key contributions. First, it contributes to the literature on returns to skills by exploiting the effects of unobserved skills instead of directly measuring skills, we exploit an exogenous shock that changes the skill distribution among workers with the same levels of observed skills. Second, this paper documents the role of occupational choice on gender inequality in the labor market from both demand and supply side of the market. Third, this paper provides evidence of symmetric effects of positive and negative shocks to education opportunities on education and labor market outcomes of compliers.

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Appendix

A Figures

Figure 1: Effects of the Quota on College Attendance Rate by Gender

Note: Figure shows the probability of college attendance for women (left) and men (right) around the cutoff. Each dot represents the college attendance rate for each birth cohort. Solid lines show linear fits with slopes and intercepts allowed to differ at both sides of the cutoff.
Source: Calculation by the authors using Iranian Labor Force Survey (ILFS).

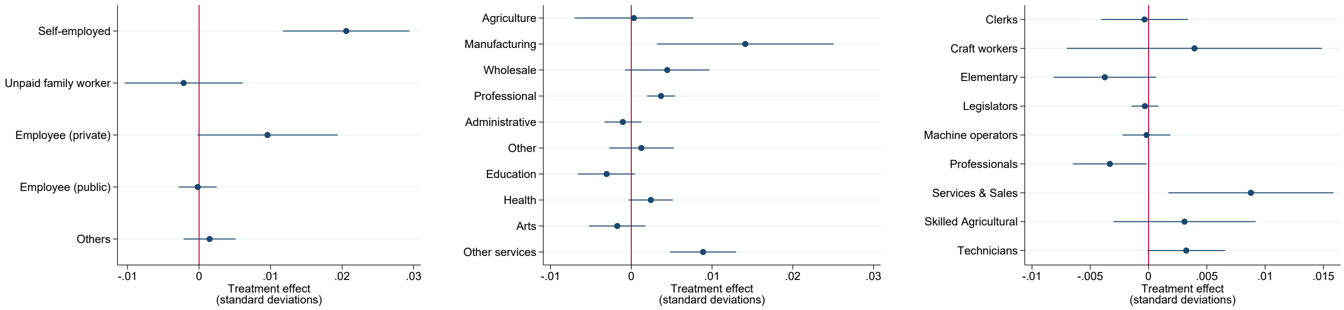
Figure 2: Effects of Women's Employment Outcomes (among HSG)

(a) LFP (b) Employment rate (c) Unemployment rate

Note: Figure shows women's labor force participation, employment, and unemployment rates among high school graduates.
Source: Calculation by the authors using Iranian Labor Force Survey (ILFS).

Figure 3: Regression Discontinuity Estimates for Effects on Occupational Choices (among female HSG workers)

(a) by class of worker (b) by industry (c) by occupation



Note: Figure presents the quota effects on women employment rate in different occupations. Specifically, it displays estimates of coefficient ρ from Equation (1). The dependent variables are indicators for whether a woman is employed in a specified industry or occupation. The sample is women who have graduated from high school/pre-university. Control variables are individual characteristics including age, region (urban vs rural), and residence of province. For detailed estimates, see Appendix Table G.3. The bars represents 95% confidence intervals. Standard errors are clustered at the province and birth month level.
Source: Authors' estimations from ILFS data.

B Tables

Table 1: Education Quota in 2012 and the Proportion of Female College Students before the Quota

	Education Quota in 2012			First Year Students in 2011	
	Only Female(%)	Only Male(%)	Both(%)	Female(%)	Male(%)
Education	46.55	29.51	23.94	78.77	21.23
Humanities and Arts	41.19	31.87	26.94	68.14	31.86
Social Sciences	32.14	37.69	30.18	59.52	40.48
Science	30.67	28.72	40.61	67.94	32.06
Engineering	17.09	37.66	45.26	38.82	61.18
Agriculture	24.67	40.80	34.54	51.23	48.77
Health and Welfare	7.63	2.32	90.05	68.09	31.91
Services	0.51	2.83	96.66	43.52	56.48

Notes: Table presents targeted shares of female and male students in different university majors based on policy documents in 2012 and actual rates among first year students before the policy (in 2011). The 2011 statistics do not include medical schools and Islamic Azad University (IAU).
Source: Authors' calculations using university admission booklets and aggregate college students data reported by the Ministry of Science, Research, and Technology

Table 2: Effect on Education (College Enrollment) by gender

	(1)	(2)	(3)
Panel A: women			
Treated	-0.024**	-0.025**	-0.025**
	(0.012)	(0.010)	(0.010)
Pre-trend	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Trend shift	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Adjusted R	0.002	0.015	0.017
Observations	86,186	86,186	86,186
Mean control(%)	55.24		
Panel A: men			
Treated	0.001	0.002	0.002
	(0.011)	(0.010)	(0.010)
Pre-trend	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Trend shift	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Adjusted R	0.002	0.012	0.013
Observations	84,927	84,927	84,927
Mean control(%)	54.36		
Bandwidth	24	24	24
Year FE	Yes	Yes	Yes
Province FE	No	Yes	Yes
Demographic controls	No	No	Yes

Notes: Table presents the effect of the 2012 education quota on college enrollment (cutoff: Sep 1992). The dependent variables is an indicator for whether a high school graduate ever enrolls in a college program. Control variables are year and province fix effects and individual characteristics including age, father's education, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

Table 3: Effect on Education (pre-University & High School Enrollment) by gender

	PreUniversity enrollment		High School completion		High School drop-out	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: women						
Treated	-0.019***	-0.020***	-0.002	-0.001	0.000	0.012
	(0.008)	(0.008)	(0.004)	(0.004)	(0.014)	(0.014)
Pre-trend	-0.002**	-0.000	0.002***	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Trend shift	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Adjusted R-squared	0.216	0.217	0.104	0.105	0.028	0.055
Observations	99,915		210,017		10,482	
Mean control (%)	89.19		85.74		9.66	
Panel B: men						
Treated	0.003	0.002	0.002	0.002	-0.030***	-0.019**
	(0.008)	(0.008)	(0.004)	(0.004)	(0.010)	(0.008)
Pre-trend	-0.003***	-0.001	-0.002***	-0.001***	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Trend shift	-0.003**	-0.003**	0.000	0.000	0.002*	0.002**
	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
Adjusted R-squared	0.250	0.251	0.128	0.129	0.015	0.027
Observations	102,567		219,640		11,329	
Mean control (%)	85.04		81.56		5.87	
cutoff	Sep 1994		Sep 1992		Sep 1996	
Bandwidth	24	24	24	24	24	24
Province & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes	No	Yes

Notes: Table presents the effect of the 2012 education quota on the pre-university enrollment, high school completion and drop out rates by gender (cutoff: Sep 1994 for pre-university enrollment, Sep 1992 for high school completion, and Sep 1996 for high school drop out). The sample for all regressions is two years before and two years after the cutoff. The sample for pre-university (high school) enrollment is high school (lower secondary) graduates, and for drops out from high school is individuals age 15 who finished lower secondary level. Control variables are year and province fix effects and individual characteristics including age, father's education, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

Table 4: Effect on Employment and Wage by gender (among HS/pre-university graduates)

	LFP		Empl.		Unempl.		ln(Wage)			
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(4)
Panel A: women										
Treated	0.021**	0.027***	0.028***	0.029***	-0.140***	-0.130***	0.004*	0.005**	0.006***	0.004**
	(0.009)	(0.010)	(0.007)	(0.008)	(0.035)	(0.035)	(0.002)	(0.002)	(0.002)	(0.002)
Pre-trend	-0.001	-0.001*	-0.000	-0.001	0.002	0.002	-0.006***	-0.007***	-0.007***	-0.006***
	(-0.001)	(-0.001)	(-0.000)	(-0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Trend shift	0.000	0.000	0.000	0.000	-0.003	-0.003	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.017	0.018	0.015	0.016	0.081	0.085	0.720	0.723	0.728	0.757
Observations	28,306	28,306	28,306	28,306	3,490	3,490	2,084	2,084	2,084	2,084
Mean control	11.69%		5.98%		48.83%		8.97			
Panel B: men										
Treated	0.172	0.159	0.078	0.075	0.084	0.072	0.001	0.001	0.001	0.001
	(0.156)	(0.156)	(0.160)	(0.160)	(0.184)	(0.183)	(0.001)	(0.001)	(0.001)	(0.001)
Pre-trend	-0.003**	-0.003***	-0.000	-0.001	-0.002*	-0.003*	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trend shift	-0.000	-0.000	-0.002	-0.002*	0.003**	0.003**	-0.001***	-0.001***	-0.001***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.152	0.223	0.104	0.140	0.022	0.028	0.806	0.809	0.811	0.814
Observations	24,004	24,004	24,004	24,004	16,887	16,887	12,365	12,365	12,365	12,365
Mean control	49.64%		34.02%		31.47%		9.38			
Panel C: all										
Treated	0.163*	0.170*	0.077	0.078	0.100	0.101	0.002	0.001	0.001	0.002
	(0.086)	(0.087)	(0.086)	(0.086)	(0.178)	(0.176)	(0.001)	(0.001)	(0.001)	(0.001)
Pre-trend	-0.002***	-0.002***	-0.001	-0.001*	-0.001	-0.002	-0.005***	-0.005***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trend shift	0.000	0.000	-0.000	-0.000	0.001	0.001	-0.001**	-0.001***	-0.001**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.041	0.404	0.040	0.291	0.024	0.042	0.960	0.961	0.961	0.959
Observations	52,310	52,310	52,310	52,310	20,377	20,377	14,449	14,449	14,449	14,449
Mean control	28.46%		18.37%		35.45%		9.30			
Bandwidth	24	24	24	24	24	24	24	24	24	24
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes
Job Characteristics	-	-	-	-	-	-	No	No	Yes	Yes
Occupation FE	-	-	-	-	-	-	No	No	No	Yes

Notes: Table presents the effect of the 2012 Education quota on the labour market outcomes among young HS/pre-university graduates by gender (age<28 and cutoff= Sep 1992). The dependent variables are labor force participation, employment rate, unemployment rate and wage rate. Wage rates (wage per hour) are log transformed and deflated by CPI which is equals 100 in year 2011. Control variables are province and region fix effects; individual characteristics including age, gender, and urban/rural; and job characteristics for wage effects include industry fix effects and full-time vs part-time jobs. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

Table 5: Elasticities of Substitution

Panel A: *RDD Estimates (2nd & 3rd steps)*	Eq (8)		Eq (9)	
$\log\left(\frac{L^f_{ct}}{L^m_{ct}}\right)$	-0.098**	(0.047)	-0.098**	(0.047)
$log\left(\frac{L^f_{t}}{L^m_{t}}\right)$			0.352***	(0.059)
Year				
2005	0.122***	(0.046)	0.152***	(0.041)
2006	0.087**	(0.035)	0.148***	(0.025)
2007	0.070**	(0.035)	0.161***	(0.021)
2008	0.031	(0.033)	0.152***	(0.013)
2009	0.019	(0.035)	0.170***	(0.011)
2010	-0.006	(0.030)	0.175***	(0.004)
2011	-0.025	(0.032)	0.187***	(0.006)
2012	-0.049	(0.031)	0.085***	(0.010)
2013	-0.066**	(0.033)	0.075***	(0.010)
2014	-0.091***	(0.032)	0.056***	(0.008)
2015	-0.117***	(0.031)	0.037***	(0.006)
2016	-0.142***	(0.029)	0.018***	(0.004)
2017	-0.164***	(0.029)	0.003	(0.004)
Birth Cohort				
1990	-0.000	(0.007)	-0.175***	(0.024)
1991	0.005	(0.006)	-0.175***	(0.025)
1992	0.011**	(0.005)	-0.170***	(0.028)
1993	0.013***	(0.005)	-0.170***	(0.029)
Adjusted R-squared	0.961		0.961	
Panel B: *RDD Estimates (1st step)*	Eq (6)		Eq (7)	
Treated	0.099**	(0.039)	0.307***	(0.026)
Pre-trend	-0.011***	(0.003)	-0.0.86***	(0.005)
Trend shift	0.013***	(0.004)	0.067***	(0.007
Adjusted R-squared	0.937		0.958	
F-stat	323.83		776.40	

Notes: Table presents estimated elasticities of substitution using a three-step estimation. Panel B presents the estimation results of the first step (RDD analysis). Rating variables are (birth cohort-1992Q3) and (year-2012) in Eq (6) and Eq (7), respectively. Panle A presents the estimation results of the second and third steps (Eq 8 and Eq 9). Dependent variable is $log\left(\frac{w^f_{jt}}{w^m_{jt}}\right)$. The estimated effects imply an elasticity of substitution between different cohort groups of 2.1, and an elasticity of substitution between different gender groups of 9.7 Standard errors are in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

C Using HIES to Predict Worker Wages

Since the wage rate is not observable in ILFS, we use 2005-2018 Iranian Households Income and Expenditure surveys (HIES) for predicting worker wages in our main sample. We cannot use the HIES data for analyzing the effect of education quota on wages because HIES do not include month of birth which is the running variable in our regression discontinuity design.

We estimate separated Mincer/Ben-Porath wage equations for women and men using HIES (2005-2018):

$$ln\ wage_t = \beta_0 + \beta_1 K_{t-1} + \beta_2 K^2_{t-1} + \beta_3 S + \beta_4 t + \epsilon_t \qquad (12)$$

where schooling (S) is is categorized into six levels: low education (lowEdu), high school graduates (HSG), pre-university graduates (PUG), some college education (SC), college graduates (CG), and post-college studies (PC). We define years of potential experience, K, as the difference between age and years of schooling, where years of schooling is defined to be 10 years for the lowEdu group, 17 years for the HSG group, 18 years for the PUG group, 20 years for the SC group, 22 years for the CG group, and 24 years PC group (including the 6 years before school).

Since a good within sample fit is unlikely to give us much confidence in its forecasting ability for another data base, we use a nonrandom holdout sample of HIES for external validation. The idea is that if the model can provide a good forecast for a holdout sample of HIES, then it can provide a good forecast for ILFS too. Thus, we use a random subsample of HIES (75% of the sample) for the estimation and the rest of the sample for the validation. Table C.1 reports the estimated coefficients by gender. The estimated parameters have values similar to those presented in the literature. Estimated parameters shows the hourly wage rate increases with experience ($\beta_1 > 0$) at a decreasing rate ($\beta_2 < 0$) and increase with schooling ($0 < \beta_{31} < \beta_{32} < \beta_{33} < \beta_{34} < \beta_{35}$). Also, parameters are significantly different across gender, in particular, although women have on average lower wage rates, they have higher marginal returns to education and and steeper returns to experience than men. Given the estimated parameters of the wage equations, we simulate the wage rate for the validation sample. Figure C.1 presents the wage prediction for high school and preuniversity graduates age<28 years old. Due to a good fit, we use the estimated parameters to predict wage rates of workers in ILFS.

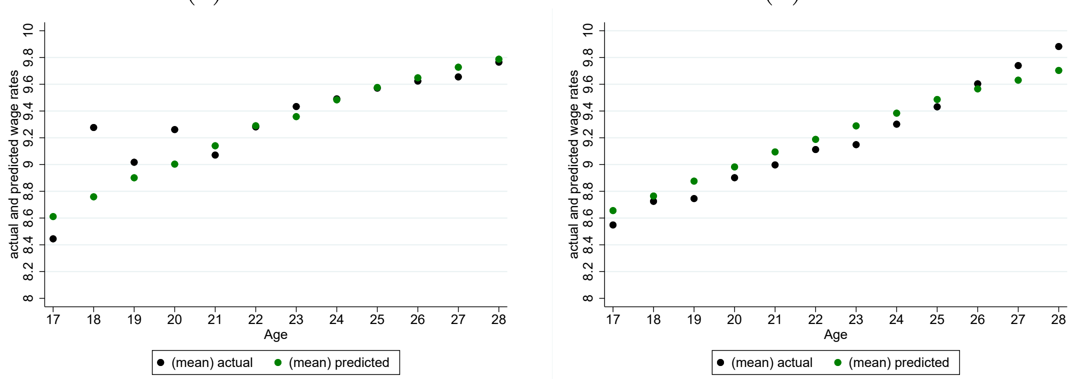
Table C.1: Wage Rates by gender

	Variables	Women	Men	H0:diff=0 (p-value)
β_0	Constant	7.771***	8.447***	0.000
		(0.029)	(0.010)	
β_1	Potential experience	0.099***	0.091***	0.002
		(0.002)	(0.001)	
β_2	Potential experience squared	-0.001***	-0.001***	0.121
		(0.000)	(0.000)	
β_{31}	HSG - schooling	0.371***	0.271***	0.003
		(0.031)	(0.007)	
β_{32}	PUG - schooling	0.644***	0.421***	0.000
		(0.020)	(0.005)	
β_{33}	SC - schooling	1.232***	0.528***	0.000
		(0.020)	(0.006)	
β_{34}	CG - schooling	1.574***	0.938***	0.000
		(0.018)	(0.006)	
β_{35}	PC - schooling	1.990***	1.373***	0.000
		(0.031)	(0.013)	
β_4	Trend parameter	-0.046***	-0.036***	0.000
		(0.001)	(0.000)	
	Observations	25,490	181,952	
	R-squared	0.315	0.221	

Notes: This table presents estimated coefficients of wage rates (Eq 12). Dependent variable, the wage rate, is log transformed and has been deflated by CPI which equals 100 in year 2011. The time period is 2005-2018. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Households Income and Expenditure Surveys (HIES).

Figure C.1: External Validation: Actual and Predicted Wage Rates by Gender

(a) women (b) men



Note: Figure presents the model's prediction of wage rates at individual ages by gender to the actual values for women (right) and men (left).
Source: Authors' calculations using Households Income and Expenditure Surveys (HIES).

D 2012 University Admission Booklet

Table D.1 Translations from 2012 Math&Physics Admission Booklet

Major	# seats	Female	Male
	University of Shahid Bahonar (Kerman)		
Computer Engineering	40	20	20
Mining Engineering	40	-	40
Architecture	20	10	10

Continued on next page

Table D.1 – *Continued from previous page*

Major	# seats	Female	Male
Mechanical Engineering	20	no quota	
Materials Engineering	40	20	20
Agricultural Engineering	48	15	33
Architectural Technician	20	10	10
Accounting	18	8	10
Chemistry	20	10	10
Economics	18	8	10
Bookkeeping	15	15	-
Management	18	8	10
Shahid Beheshti University (Tehran)			
Statistics	35	17	18
Mathematics	50	20	30
Computer Science	30	15	15
Physics	45	23	22
Electrical Engineering	60	20	40
Computer Engineering	40	16	24
Architecture	25	15	10
Accounting	30	18	12
Economics	95	38	57
Management	120	69	51
Shahid Chamran University (Ahvaz)			
Statistics	35	-	35
Mathematics	40	-	40
Computer Science	30	-	30
Physics	30	-	30
Electrical Engineering	50	-	50
Civil Engineering	25	-	25
Computer Engineering	30	-	30
Architecture	20	-	20
Mechanical Engineering	25	-	25
Materials Engineering	25	-	25
Agricultural Engineering	55	-	55
Accounting	30	-	30
I/O Psychology	25	-	25
Chemistry	30	-	30
Economics (Business)	25	-	25

Continued on next page

Table D.1 – *Continued from previous page*

Major	# seats	Female	Male
Economics (Theory)	25	25	-
Bookkeeping	25	-	25
Management	25	-	25
Shiraz University (Shiraz)			
Statistics	30	13	17
Mathematics	45	27	18
Physics	25	10	15
Electrical Engineering	76	32	44
Urban Engineering	25	10	15
Civil Engineering	25	10	15
Computer Engineering	37	17	20
Architecture	20	8	12
Mechanical Engineering	55	20	35
Materials Engineering	25	10	15
Oil Engineering	25	10	15
Agricultural Engineering	77	32	45
Accounting	17	7	10
Economics	30	13	17
Bookkeeping	27	11	16
Management	34	14	20
Power and Water University of Technology (Tehran)			
Electrical Engineering	65	15	50
Civil Technician	35	5	30
Civil Engineering	50	10	40
Computer Engineering	40	10	30
Mechanical Engineering	55	10	45
Isfahan University of Technology (Isfahan)			
Statistics	20	10	10
Mathematics	20	10	10
Physics	40	20	20
Electrical Engineering	100	30	70
Industrial Engineering	45	13	32
Civil Engineering	50	no quota	
IT Engineering	20	6	14
Computer Engineering	40	12	28
Mining Engineering	20	-	20

Continued on next page

Table D.1 – *Continued from previous page*

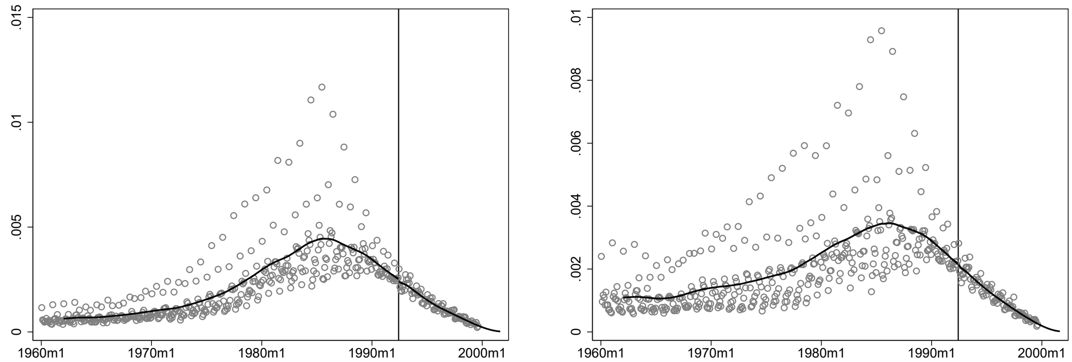
Major	# seats	Female	Male
Mechanical Engineering	100	no quota	
Materials Engineering	40	no quota	
Textile Engineering	60	18	42
Agricultural Engineering	40	-	40
Chemistry	20	10	10

Notes: Table presents translations of pages 28-29 of 2012 math & physics admission booklet. The National Organization of Educational Testing (Sanjesh) publishes admission booklets separately for different groups of majors related to three university entrance exams: humanities, math&physics, and natural sciences. 2012 admission booklets list all majors at different universities (sorted by alphabetical order) and provide quota information for each program including total seats and reserved seats for each gender. We select these two pages because they include some top rank universities in metropolises (Tehran, Isfahan, Shiraz, Ahvaz, and Kerman). These information combined with gender distribution of first-year students in 2011 can show the magnitude of the quota. For example in 2011, women made up 39% of first-year students in engineering at the Shahid Chamran University (Source: Institute for Research and Planning in Higher Education). The 2012 gender quota made all engineering majors at this university male-only. As another example, the quota divided seats in sciences (Statistics, Mathematics, Physics, and Chemistry) equally between female and male students at Isfahan University of Technology, even though women made up 60% of first-year science students at this university in 2011 (Source: Institute for Research and Planning in Higher Education).
Source: Authors' translations from 2012 admission booklets.

E Identification Assumptions

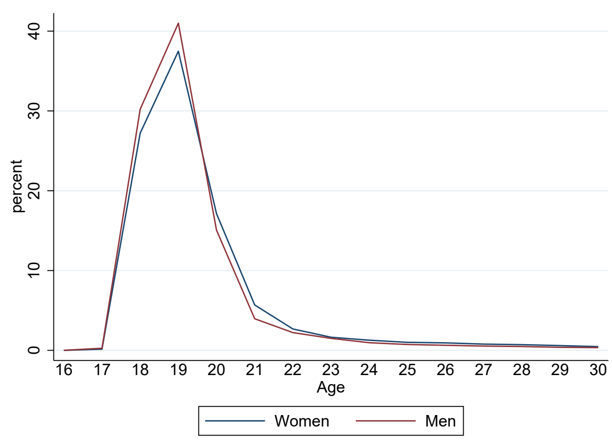
Figure E.1: Distribution of Birth Months by Gender

(a) women (b) men



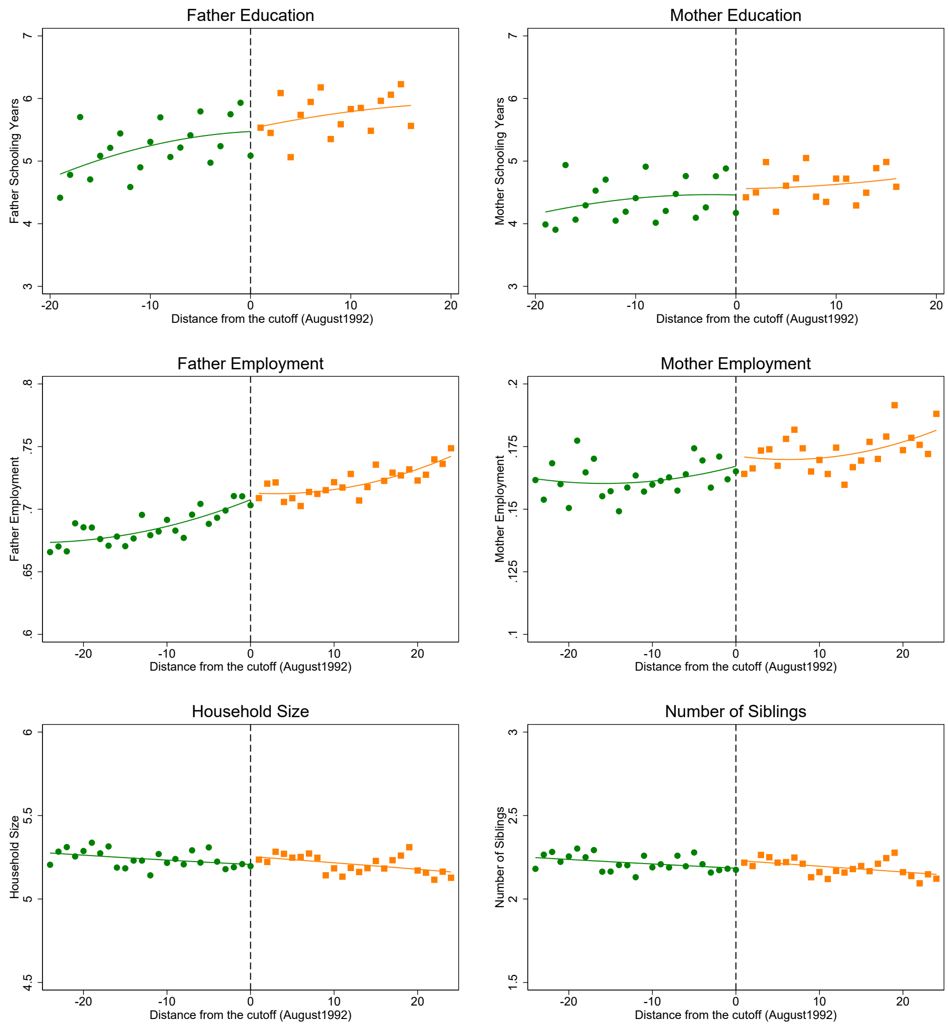
Note: Figure shows the distribution of the running variable (birth month) separately for women (right) and men (left).
Source: Calculation by the authors using Iranian Labor Force Survey (ILFS).

Figure E.2: Age Distribution of 2012 University Applicants by Gender



Note: Figure shows the age distribution of 2012 university applicants for women (blue) and men (red). We limited observations to applicants' age 16-30; less than one percent of applicants are above 30 years old. 84% of applicants are 20 years old or younger (82% of female and 87% of male candidates). The average and median age is 19 years old, and there is no gender differences.
Source: Iranian University Applicants Data, the figure is reproduced by authors.

Figure E.3: Effects of the Quota on Covariates



Note: Figure shows that covariates (parents' education, parents' work status, and family size) change smoothly across the cutoff. Each dot represents the average values for each birth cohort.
Source: Calculation by the authors using Iranian Labor Force Survey (ILFS).

F Decomposing Employment and Wage Changes into Cohort, Age, and Time Effects

The change in the gender gap in labor market outcomes for different cohorts (defined by the individual's year of birth) can be related to different age and year effects. To investigate the potential role of cohort effects in explaining the gender gap in labor market outcomes among high-school graduates, we use two approaches to decompose the gender gap into cohort, age, and time effects. As the first identification approach, we follow Card and Lemieux (2001) by regressing the cohort-level wage gap on year, cohort, and age effects:

$$log\left(\frac{y_{ct}^{m}}{y_{ct}^{f}}\right) = C_c + T_t + A_{t-c} + \epsilon_{t,c} \tag{13}$$

where y_{ct}^{f} and y_{ct}^{m} are labour market outcomes (participation, employment, and average weekly earning) of female and male HSG of birth cohort c in year t, respectively. Since labor market outcomes among men are higher that that of women, bigger $log\left(\frac{y_{ct}^{m}}{y_{ct}^{f}}\right)$ shows bigger gender gap. Since cohort (birth year) is a linear combination of the individual's age and the year, we use four-year cohort intervals and assume that cohort and age effects are constant within each interval to resolve the identification issue. As the second identification approach, we follow MaCurdy and Mroz (1995) and Fitzenberger et al. (2001) and consider a polynomial function of c (the linear cohort effect is assumed to be zero), as well as interaction terms between age and cohorts:

$$log\left(\frac{y_{ct}^{m}}{y_{ct}^{f}}\right) = T_t + A_a + \Sigma_{i=1}^{4}\gamma_i R_{i,at} + \xi_{at}K_{after}(c_{at}) + (1-\xi_{at})K_{before}(c_{at}) + \nu_{t,c} \tag{14}$$

where ξ_{at} is a dummy variable for being born after the cutoff, K_{after} and K_{before} are polynomial function of cohorts, and $R_{i,at}$ capture polynomial interaction terms between age and cohorts.[42] Table F.1 present the estimation results from these two approaches. The estimated effects and the test for joint significance of all cohort terms ($H_0 : \gamma_i = \delta_{after,j} = \delta_{before,j} = 0$ for all i, j) show evidence for the cohort effect in the labor market outcomes (LFP, employment, and wage rate) gender gap. In particular, gender gaps significantly decrease compare among young HSG cohorts who were born after September 1992.

[42] $K_k(c_{at}) = \delta_{k,1}c_{at}^2 + \delta_{k,2}c_{at}^3 \quad$ and $k \in \{after, before\}$
$R_1 = ca^2/2 + a^3/3$
$R_2 = c^2a^2/2 + 2a^3c/3 + a^4/3$
$R_3 = ca^3/3 + a^4/4$
$R_4 = c^2a^3/3 + a^4c/2 + a^5/5$

Table F.1: Decompositions of Gender Employment and Wage Gap (among HS/pre-university graduates) into Cohort, Age, and Time Effects

	Log. Relative LFP		Log. Relative Employment		Log. Relative Wage	
	Model(1)	Model(2)	Model(1)	Model(2)	Model(1)	Model(2)
VARIABLES	Eq(13)	Eq(14)	Eq(13)	Eq(14)	Eq(13)	Eq(14)
Cohort						
Sep1991-Aug1992	0.141		0.052		0.034	
	(0.191)		(0.097)		(0.022)	
Sep1992-Aug1993	-0.395***		-0.095***		-0.149*	
	(0.081)		(0.002)		(0.078)	
Sep1993-Aug1994	-0.346***		-0.118***		-0.152*	
	(0.025)		(0.009)		(0.071)	
Year						
2009-2011	-0.508	0.022	0.269*	0.524**	0.066	0.027
	(0.343)	(0.209)	(0.151)	(0.223)	(0.039)	(0.042)
2012-2014	0.166	0.013	0.576**	0.761**	-0.046	0.052
	(0.521)	(0.314)	(0.235)	(0.329)	(0.059)	(0.063)
2015-2017	-0.043	-0.484	0.478	0.441	-0.006	0.057
	(0.372)	(0.391)	(0.314)	(0.411)	(0.042)	(0.078)
Age						
18-20	0.378	0.333	0.001	0.120	0.010	-0.026
	(0.343)	(0.198)	(0.151)	(0.186)	(0.039)	(0.040)
21-23	0.635	0.084	0.043	0.038	0.043	-0.037
	(0.483)	(0.301)	(0.235)	(0.306)	(0.055)	(0.060)
24-27	0.720)	0.249	-0.032	-0.153	0.072	-0.031
	(0.609	(0.386)	(0.314)	(0.401)	(0.069)	(0.077)
R1		-0.051***		-0.015*		-0.001**
		(0.008)		(0.007)		(0.000)
R2		0.002***		0.001*		0.000
		(0.000)		(0.000)		(0.000)
R3		0.003***		0.001*		0.000*
		(0.000)		(0.000)		(0.000)
R4		0.000***		0.000*		-0.000
		(0.000)		(0.000)		(0.000)
cohortA2		0.243		-0.13		0.040
		(0.272)		(0.147)		(0.050)
cohortB2		-0.270***		-0.035		-0.021**
		(0.063)		(0.054)		(0.009)
Constant	1.582***	13.507***	1.517***	5.226***	0.358***	0.058
	(0.152)	(1.801)	(0.102)	(1.840)	(0.017)	(0.361)
Any cohort effects	2.28**	13.18***	2.95**	4.31**	2.30*	3.43*

Notes: Table presents estimated coefficients of cohort, time, and age using two decomposition approaches (Eq 13 and Eq 14). The estimated effects and test for joint significance of all cohort terms ($H_0 : \gamma_i = \delta_{after,j} = \delta_{before,j} = 0$ for all i, j) show evidence for cohort effect in the employment and wage gender gap. Standard errors are in parentheses. The base (omitted) year, cohort, and age group are years 2006-2008, oldest birth cohort (Sep1990-Aug1991), and age 28+. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

G Effects on Occupational Choices

Table G.1: Percentage of HSG Female Workers in Different Classes, Industries, and Occupations

	Total	Control	Treated	Diff	H0:Diff=0
Panel A: Classes					
Self-employed worker	28.31	20.55	31.54	10.99	0.000
Unpaid family worker	28.02	36.54	24.47	-12.07	0.000
Employee in Private sector	35.84	33.77	36.71	2.94	0.202
Employee in Public sector	3.07	2.28	3.40	1.12	0.179
Other (Employer, Employee in Cooperative sector, Trainee)	4.75	6.85	3.87	-2.98	0.000
Panel B: Industries					
Agriculture	20.36	24.63	18.57	-6.06	0.000
Manufacturing	41.96	43.23	41.43	-1.80	0.448
Wholesale and retail	11.38	9.30	12.24	2.94	0.054
Arts, entertainment and recreation	2.98	7.67	1.02	-6.65	0.000
Education	3.70	4.08	3.54	-0.54	0.551
Administrative and Support	1.78	3.92	0.88	-3.04	0.000
Health	3.46	1.63	4.22	2.59	0.000
Professional, scientific and technical activities	1.49	0.00	2.11	2.11	0.000
Other service activities	6.91	0.00	9.80	9.80	0.000
Other [43]	6.00	5.56	6.19	0.63	0.573
Panel C: Occupations					
Manual					
Craft and related trades workers	35.87	40.46	33.36	-7.10	0.003
Elementary occupations	7.48	7.01	7.74	0.73	0.583
Skilled Agricultural, Forestry and Fishery Workers	18.77	19.25	18.51	-0.74	0.704
Plant and machine operators and assemblers	1.96	1.31	2.31	1.00	0.147
Service					
Services and Sales Workers	20.61	16.48	22.86	6.38	0.002
White-collar					
Legislators, senior officials and managers	0.52	0.65	0.44	-0.21	0.565
Technicians and associate professionals	5.24	4.24	5.78	1.54	0.168
Clerical Support Workers	5.76	6.85	5.16	-1.69	0.148
Professionals	3.80	3.75	3.83	0.08	0.939

Notes: Table presents shares of female workers in different occupations.
Source: Authors' calculations from ILFS data.

Table G.2: Gender Distribution in Different Occupations

	Control			Treated				
	(1)	(2)	(3)	(4)	(5)	(6)	Diff	H0:Diff=0
Occupations	Total	Women	Men	Total	Women	Men	(5)-(2)	(p-value)
Manual								
Craft and related trades workers	25.02	17.18	82.82	25.34	18.34	81.66	1.16	0.23
Elementary occupations	21.90	3.76	96.24	19.82	4.96	95.04	1.20***	0.03
Skilled Agricultural, Forestry and Fishery Workers	15.90	10.55	89.45	19.72	12.89	87.11	2.34***	0.02
Plant and machine operators and assemblers	4.73	2.97	97.03	9.76	3.15	96.85	0.18	0.79
Service								
Services and Sales Workers	15.40	17.90	82.10	12.79	21.89	78.11	3.99***	0.00
White-collar								
Legislators, senior officials and managers	4.73	0.95	99.05	7.38	0.67	99.33	-0.28	0.55
Technicians and associate professionals	3.03	27.81	72.19	2.65	25.84	74.16	-1.97	0.56
Clerical Support Workers	2.16	35.42	64.58	1.70	39.18	60.82	3.76	0.41
Professionals	1.04	54.94	45.06	0.84	58.82	41.18	3.88	0.56
Total	100.00	12.10	87.90	100.00	13.18	86.82	1.08***	0.01

Notes: Table presents proportion of women and men in different occupations among control and treated cohorts.
Source: Authors' calculations from ILFS data.

Table G.3: Effects on Occupational Choices

Dependent var	coefficient	std
Panel A: Classes		
Self-employed worker	0.021***	(0.004)
Unpaid family worker	-0.002	(0.004)
Employee in Private sector	0.010*	(0.005)
Employee in Public sector	0.000	(0.001)
Other (Employer, Employee in Cooperative sector, Trainee)	0.001	(0.002)
Panel B: Industries		
Agriculture	0.000	(0.004)
Manufacturing	0.014**	(0.006)
Wholesale and retail	0.004*	(0.003)
Arts, entertainment and recreation	-0.002	(0.002)
Education	-0.003*	(0.002)
Administrative and Support	-0.001	(0.001)
Health	0.002*	(0.001)
Professional, scientific and technical activities	0.004***	(0.001)
Other service activities	0.009***	(0.002)
Other	0.001	(0.002)
Panel C: Occupations		
Manual		
Craft and related trades workers	0.004	(0.006)
Elementary occupations	-0.004*	(0.002)
Skilled Agricultural, Forestry and Fishery Workers	0.003	(0.003)
Plant and machine operators and assemblers	-0.000	(0.001)
Service		
Services and Sales Workers	0.009**	(0.004)
White-collar		
Legislators, senior officials and managers	-0.000	(0.001)
Technicians and associate professionals	0.003*	(0.002)
Clerical Support Workers	-0.000	(0.002)
Professionals	-0.003**	(0.002)

Notes: Table presents the estimated quota effects on occupational choices: class of workers, industry, and occupation. The dependent variables are indicators for whether a HSG workers works in specific occupation. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from ILFS data.

Table G.4: Average Wage Rates of HSG Workers in Different Occupations

	All	Women	Men
Manual			
Craft and related trades workers	9.867	9.448	9.960
	(0.436)	(0.419)	(0.383)
Elementary occupations	9.891	9.460	9.911
	(0.388)	(0.41)	(0.375)
Skilled Agricultural, Forestry and Fishery Workers	9.873	9.338	9.935
	(0.455)	(0.397)	(0.419)
Plant and machine operators and assemblers	10.075	9.493	10.086
	(0.362)	(0.423)	(0.35)1
Service			
Services and Sales Workers	9.994	9.506	10.067
	(0.441)	(0.438)	(0.392)
White-collar			
Legislators, senior officials and managers	10.068	9.901	10.075
	(0.473)	(0.470)	(0.472)
Technicians and associate professionals	10.130	9.678	10.229
	0.439)	(0.448)	(0.370)
Clerical Support Workers	10.150	9.700	10.270
	(0.439)	(0.447)	(0.350)
Professionals	10.150	9.909	10.324
	(0.457)	(0.477)	(0.352)
Total	9.985	9.565	10.043
	(0.438)	(0.466)	(0.401)

Notes: Table presents the average wage rates (log transferred and deflated by CPI which is equals 100 in year 2011) of HSG workers in different occupations (standard deviation in parentheses). The sample is all HSG workers over years 2005-2018.
Source: Authors' calculations from ILFS data.

Table G.5: Effects on Working preferences (unemployed women)

Dependent var	coefficient	std
Ideal Working Hours	-1.345	(0.985)
Ideal Employment Status		
Employee	-0.061	(0.037)
Self-employed	0.060	(0.037)
Ideal Job Sector		
Agricultural	0.005	(0.016)
Industry	0.004	(0.036)
Services	-0.014	(0.035)
Observations	1,398	

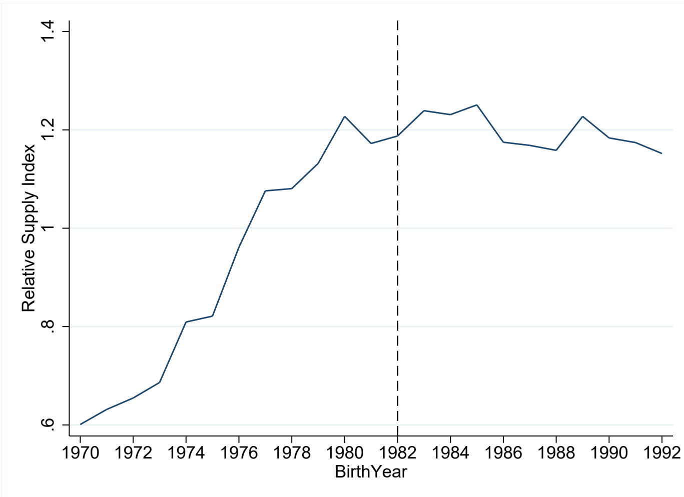
Notes: Table presents the estimated quota effects (ρ in Eq(1)) on working preferences: ideal working hours, ideal employment status (being employee or self-employed), and ideal job sector (agricultural, industry, services). The sample is limited to unemployed individuals because in our data only this group are asked about their preferences. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from ILFS data.

[43] Including information, social security, energy supply, construction, transportation, food services, financial, real estate, and activities of Households as Employers. there is no female workers in mining and water supply industries.

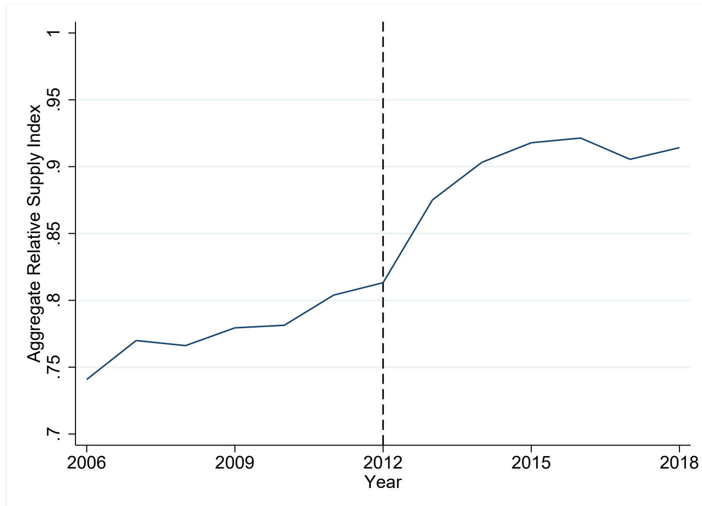
H Labor Market Changes for College Graduates

Figure H.1: Relative Supply of Female Workers
(among college graduates labour force)

(a) Relative Supply

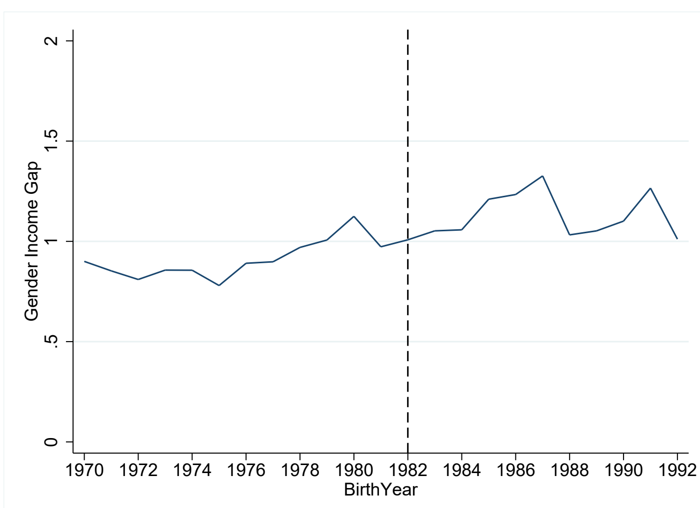


(b) Aggregate Relative Supply



Note: Figure reports the trends of relative supply of female labour force among college graduates labour force (2 and 4-year university programs). Figures (a) shows while among pre-1982 cohorts the women's labor supply was increasing, it remain stable around 1.2 among post-1982 birth cohorts. Figures (b) plots the aggregate relative supply index. The decreasing trend of this index turned get steeper for some years after the policy but eventually get falt due to reduction women's university enrollment.
Source:Authors' calculations from ILFS data.

Figure H.2: Gender Income Gap
(among college graduates workers)



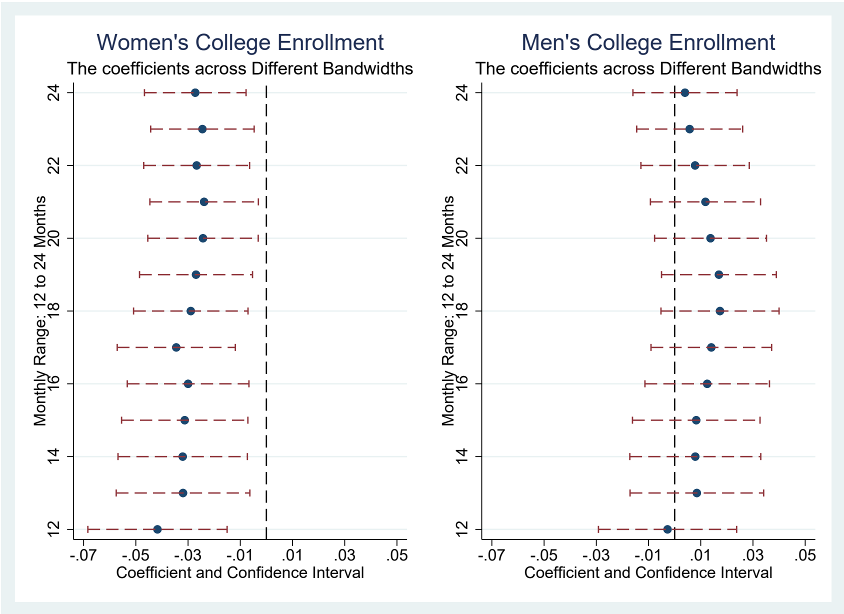
Note: Figure reports the gender gap in real income per hour (male workers income/female workers income) among young ($age \leq 28$) college graduates.
Source:Authors' calculations from HIES data.

I Robustness Checks

I.1 Different Bandwidth and Different Model Specifications

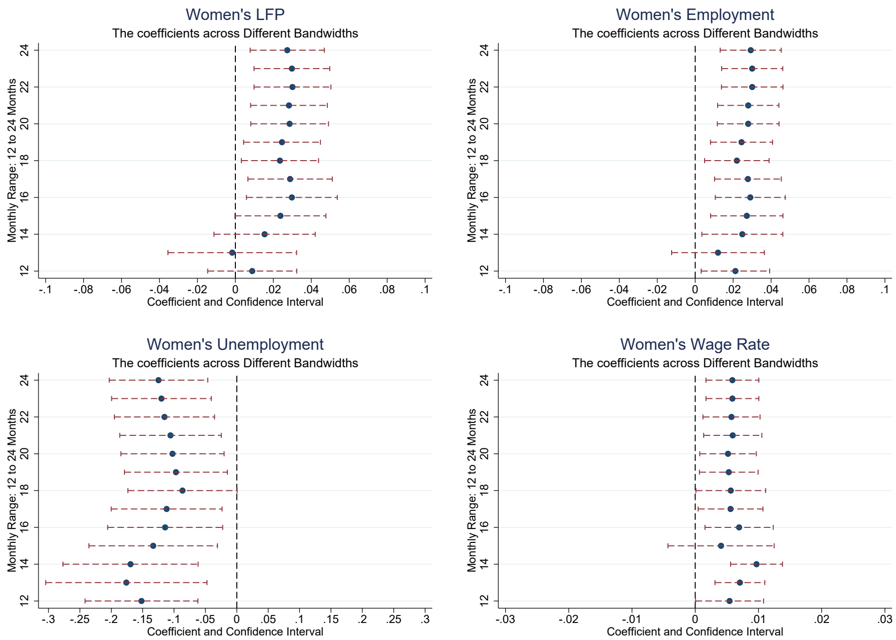
We examine the sensitivity of our RD estimates to different bandwidths and different specifications for the smooth functions.

Figure I.1: Effects on College Enrollment (different bandwidth: 12-24 months)



Note: Figure reports the quota effects on college enrollment using different bandwidths. Specifically, it displays estimates of coefficient ρ from Equation (1) using 12 to 24 months bandwidths around the cusoff (Sep 1992). For detailed estimates using h=12 months, see Table I.1. The bars represents 95% confidence intervals. Standard errors are clustered at the province and birth month level.
Source: Authors' estimations from ILFS data.

Figure I.2: Effects on Women's Employment and Wage Rate (different bandwidth: 12-24 months)



Note: Figure reports the quota effects on employment outcomes using different bandwidths. Specifically, it displays estimates of coefficient ρ from Equation (1) using 12 to 24 months bandwidths around the cusoff (Sep 1992). For detailed estimates using h=12 months, see Table I.1. The bars represents 95% confidence intervals. Standard errors are clustered at the province and birth month level.
Source: Authors' estimations from ILFS data.

Table I.1: Effect on Education and Employment (bandwidth=12 months)

	College Enrollment	PreUniversity Enrollment	High School drop-out	LFP	Empl.	Unempl.	ln(wage)
Panel A: women							
Treated	-0.042***	-0.040***	0.020	0.083*	0.021**	-0.152***	0.005**
	(0.014)	(0.009)	(0.030)	(0.045)	(0.009)	(0.045)	(0.002)
Baseline Mean (%)	56.03	88.86	10.38	11.19%	5.84%	47.80%	8.93
Adjusted R-squared	0.018	0.256	0.071	0.024	0.023	0.119	0.740
Observations	43,572	50,922	5,254	13,503	13,503	1,705	1,028
Panel B: men							
Treated	-0.003	0.013	-0.054***	0.213	0.198	0.258	-0.002
	(0.014)	(0.010)	(0.019)	(0.269)	(0.156)	(0.194)	(0.002)
Baseline Mean (%)	54.36	84.66	5.49	46.20%	32.41%	29.85%	9.34
Adjusted R-squared	0.011	0.285	0.029	0.226	0.138	0.029	0.719
Observations	42,588	52,045	5,719	11,677	11,677	8,529	6,363
cutoff	Sep 1992	Sep 1994	Sep 1996	Sep 1992	Sep 1992	Sep 1992	Sep 1992
Bandwidth	12	12	12	12	12	12	12
Province & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job Characteristics	-	-	-	-	-	-	-

Notes: Table presents the effect of the 2012 education quota on different education outcomes (college enrollment, preuniversity enrollment, and high school drop-out rates) and employment outcomes (LFP, employment rate, unemployment rate) using h=12 months bandwidth. Control variables are year and province fix effects and individual characteristics including age, father's education, urban/roral, and born in the 1^{st} half or 2^{nd} half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from ILFS data.

Table I.2: Effect on College Enrollment (different functional forms & using sample weights)

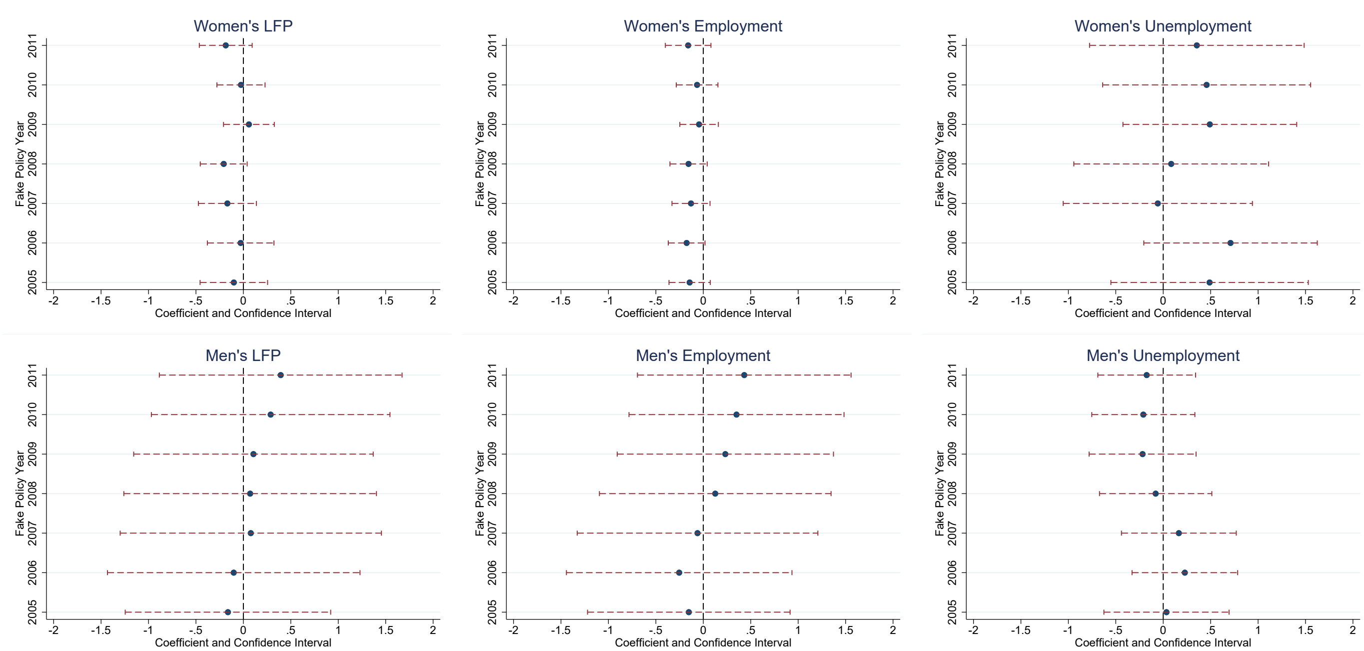
	Linear		Quardratic		Cubic		using Sample Weight		
	Linear	Interaction	Quadratic	Interaction	Cubic	Interaction	(1)	(2)	(3)
Panel A: women									
Treated	-0.030***	-0.027***	-0.024**	-0.030**	-0.028**	-0.035*	-0.046**	-0.048***	-0.048***
	(0.010)	(0.010)	(0.010)	(0.015)	(0.013)	(0.020)	(0.018)	(0.017)	(0.016)
F-stat	18.56	18.10	17.85	15.76	17.68	17.75	10.01	10.62	15.54
Adjusted R-squared	0.014	0.017	0.018	0.015	0.017	0.018	0.001	0.016	0.021
Panel B: men									
Treated	0.002	0.004	0.004	0.015	0.017	-0.018	0.006	0.003	0.004
	(0.010)	(0.010)	(0.010)	(0.014)	(0.013)	(0.018)	(0.016)	(0.016)	(0.016)
F-stat	13.00	12.68	11.42	12.53	12.44	11.74	9.00	9.51	11.83
Adjusted R-squared	0.010	0.012	0.013	0.012	0.012	0.012	0.001	0.011	0.014
Bandwidth	24	24	24	24	24	24	24	24	24
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Effect	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes

Notes: Table presents the effect of the 2012 education quota on college enrollment (cutoff: Sep 1992) with different functional form of the smooth function. For the main results we do not use sample weights. As for robustness check we run linear regression using weights and find similar results (three last columns). Control variables are year and province fix effects and individual characteristics including age, father's education, urban/rural, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

I.2 Placebo Tests

We conduct placebo tests by using the pre-reform data to examine effects at placebo cutoff values.

Figure I.3: Placebo Effect on Employment using pre-treated periods



Note: Figure reports the effect on HS/pre-university graduates' employment outcomes using fake policy years (2005-2011), and thus placebo cutoffs (Sep 1985-1991). Control variables are year and province fix effects and individual characteristics including age, urban/rural, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. For detailed estimates using fake policy year 2011, see Table I.4. The bars represents 95% confidence intervals.
Source: Authors' estimations from ILFS data.

Table I.3: Effect on Labor Supply with different functional forms

	Linear	Linear interaction	Quadratic	Quadratic interaction	Cubic	Cubic interaction
Panel A: aggregate LS						
Treated	1.102***	0.756***	0.937***	0.743***	1.030***	0.727***
	(0.025)	(0.027)	(0.029)	(0.016)	(0.021)	(0.010)
(Birth Cohort-cutoff)	-0.128***	-0.170***	-0.106***	-0.429***	-0.227***	-0.680***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.009)
Treated × (Birth Cohort-cutoff)		0.162***		0.437***		0.744***
		(0.009)		(0.015)		(0.019)
(Birth Cohort-cutoff)^2			0.008***	-0.046***	0.011***	-0.155***
			(0.001)	(0.001)	(0.001)	(0.004)
Treated × (Birth Cohort-cutoff)^2				0.044***		0.127***
				(0.002)		(0.008)
(Birth Cohort-cutoff)^3					0.004***	-0.010***
					(0.000)	(0.000)
Treated × (Birth Cohort-cutoff)^3						0.013***
						(0.001)
F-stat	970.520	1225.369	804.807	3639.003	1242.407	8001
Adjusted R-squared	0.813	0.892	0.844	0.976	0.918	0.992
Panel B: cohort-specific						
Treated	1.226***	0.753***	0.962***	0.749***	1.144***	0.751***
	(0.035)	(0.041)	(0.039)	(0.043)	(0.038)	(0.047)
(Birth Cohort-cutoff)	-0.048***	-0.062***	-0.039***	-0.166***	-0.082***	-0.301***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)	(0.013)
Treated × (Birth Cohort-cutoff)		0.065***		0.170***		0.303***
		(0.004)		(0.012)		(0.024)
(Birth Cohort-cutoff)^2			0.001***	-0.008***	0.001***	-0.032***
			(0.000)	(0.000)	(0.000)	(0.002)
Treated × (Birth Cohort-cutoff)^2				0.007***		0.032***
				(0.001)		(0.003)
(Birth Cohort-cutoff)^3					0.000***	-0.001***
					(0.000)	(0.000)
Treated × (Birth Cohort-cutoff)^3						0.001***
						(0.000)
F-stat	624.189	736.383	572.660	842.675	576.902	785.368
Adjusted R-squared	0.740	0.834	0.796	0.906	0.840	0.926
Bandwidth	24	24	24	24	24	24
Province & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the effects on labor supply using different specifications for the smooth function. The dependent variable is cohort-specific labor supply, $log\left(\frac{L^f_{jt}}{L^m_{jt}}\right)$, in panel A, and aggregate labor supply, $log\left(\frac{L^f_t}{L^m_t}\right)$, in panel B.
*Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from ILFS data.

Table I.4: Placebo Effect on Women's Education and Employment using Fake Policy Year 2011

	College Enrollment	LFP	Empl.	Unempl.	ln(wage)
Treated	-0.017	-0.186	-0.160	0.354	-0.078
	(0.014)	(0.142)	(0.122)	(0.575)	(0.086)
Adjusted R-squared	0.015	0.016	0.012	0.072	0.665
Observations	50,437	15,436	15,436	1,889	1,103
Baseline Mean (%)		12.76	8.20	35.75	9.00
fake cutoff	Sep 1991	Sep 1991	Sep 1991	Sep 1991	Sep 1991
Bandwidth	12	12	12	12	12
Province & Year FE	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes

Notes: Table presents the effect on education and employment outcomes using fake policy year 2011, and thus placebo cutoffs. Control variables are year and province fix effects and individual characteristics including age, urban/rural, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses.
*Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

Table I.5 shows that lifting quotas in 2015 slightly reduce men's college enrollemnt, while there is no significant effect on women's.

Table I.5: Effect of Lifting Quotas in 2015 on Education (College Enrollment) by gender

	(1)	(2)	(3)
Panel A: women			
Treated	-0.025	-0.024	-0.024
	(0.017)	(0.015)	(0.015)
Adjusted R-squared	0.001	0.027	0.034
Observations	40,570	40,570	40,570
Panel B: men			
Treated	-0.027*	-0.024*	-0.020
	(0.015)	(0.014)	(0.014)
Adjusted R-squared	0.002	0.02	0.03
Observations	41,052	41,052	41,052
Birth cutoff	Sep 1995	Sep 1995	Sep 1995
Bandwidth	24	24	24
Province FE	Yes	Yes	Yes
Age Effect	No	Yes	Yes
Demographic controls	No	No	Yes

Notes: Table presents the effect of lifting quotas in 2015 on college enrollment (cutoff: Sep 1995). The dependent variables is an indicator for whether a high school graduate ever enrolls in a college program. Control variables are year and province fix effects and individual characteristics including age, urban/rural, and born in the 1st half or 2nd half of the year. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

I.3 Migration

One important concern is that endogenous migration could bias the results. Affected women may go to other provinces or other countries to continue their education. In this section, we provide evidence of no change in migration pattern. Our data include limited information on the migration. We observe the data on previous location only for those who moved recently (last survey year). Thus, we limited our data to academic year 2011 for control and 2012 for treated group. As Table I.6 shows, female students' migration within and across provinces is not changed significantly. Also, the quotas have no effects on female immigration to other countries.

Table I.6: Migration Pattern Among College Students

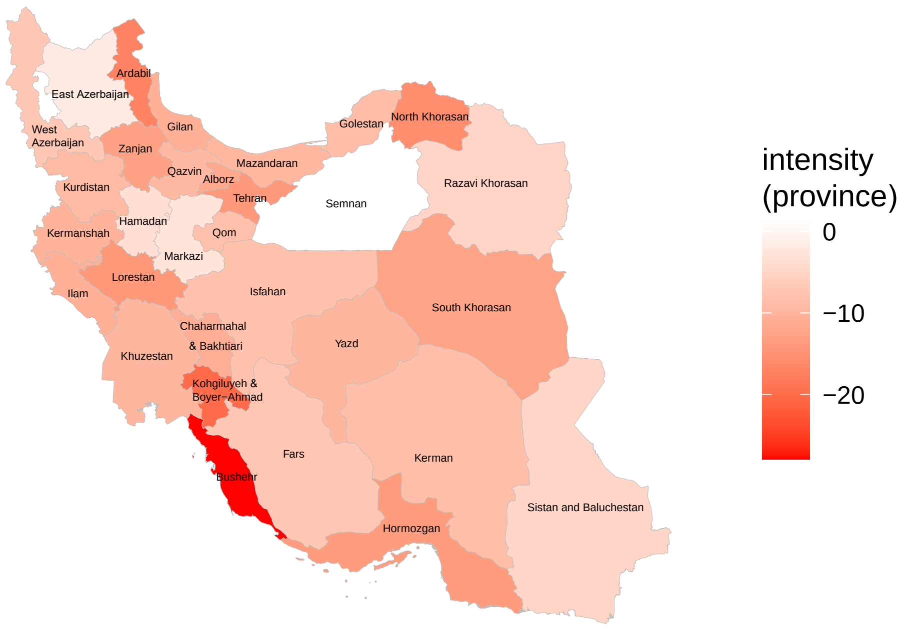
	Women			Men		
location	control	treated	Diff	control	treated	Diff
same city/village	76.65	82.44	5.79**	68.62	77.43	8.81***
same province, another city/village	14.27	10.69	-3.58	14.97	11.43	3.54*
another province	8.68	5.73	-2.95	14.49	9.14	-5.35**
abroad	0.40	1.15	0.75	1.92	2.00	0.08

Notes: Table presents the percentage of female and male college students among control and treated groups, as well the difference. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

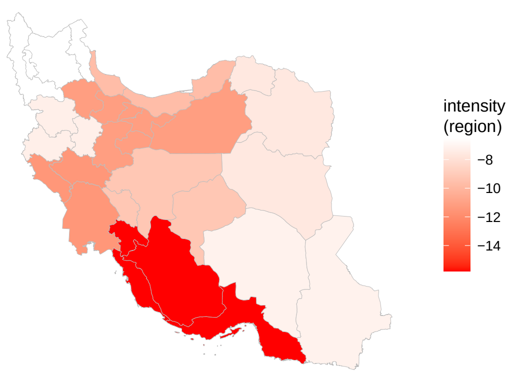
J Heterogeneous Effects

Figure J.1: Map of Iranian Provinces/Regions/Territories showing the Intensity of the 2012 Education Quota

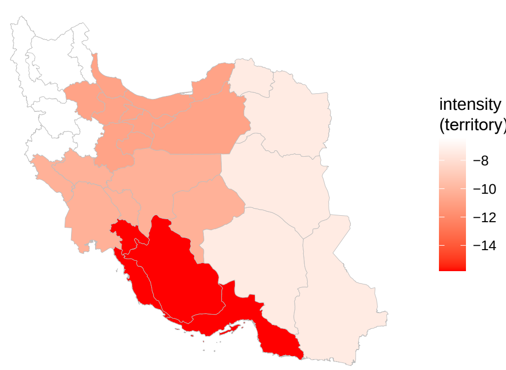
(a) at province level



(b) at region level



(c) at territory level



Note: Figure shows the intensity of the 2012 education quota across provinces, regions, and territories. For more details, see Table J.1.
Source: Authors' calculation using university admission booklets and aggregate college students data reported by the Ministry of Science, Research, and Technology

Table J.1: The Intensity of the 2012 Education Quota across Provinces/Regions/Territories

Province name	Province code	Region code	Territory code	intensity province	intensity region	intensity territory
Tehran	6	1	1	-14.05	-11.15	-10.89
Zanjan	12	1	1	-12.82	-11.15	-10.89
Semnan	13	1	1	1.32	-11.15	-10.89
Qazvin	16	1	1	-9.5	-11.15	-10.89
Qom	17	1	1	-8.3	-11.15	-10.89
Markazi	26	1	1	-2.85	-11.15	-10.89
Alborz	30	1	1	-11.78	-11.15	-10.89
Golestan	22	9	1	-8.86	-9.7	-10.89
Gilan	23	9	1	-10.69	-9.7	-10.89
Mazandaran	25	9	1	-9.62	-9.7	-10.89
Sistan and Baluchestan	14	4	2	-5.05	-7.16	-7.45
Kerman	19	4	2	-8.59	-7.16	-7.45
South Khorasan	8	8	2	-12.58	-7.63	-7.45
Razavi Khorasan	9	8	2	-5.19	-7.63	-7.45
North Khorasan	10	8	2	-15.62	-7.63	-7.45
East Azerbaijan	0	2	3	-1.82	-6.52	-6.44
West Azerbaijan	1	2	3	-7.22	-6.52	-6.44
Ardabil	2	2	3	-17.15	-6.52	-6.44
Kurdistan	18	6	3	-9.18	-7.31	-6.44
Kermanshah	20	6	3	-10.26	-7.31	-6.44
Hamadan	28	6	3	-3.68	-7.31	-6.44
Isfahan	3	3	4	-8.22	-9.24	-10.24
Chaharmahal and Bakhtiari	7	3	4	-10.87	-9.24	-10.24
Yazd	29	3	4	-9.76	-9.24	-10.24
Ilam	4	7	4	-10.67	-11.48	-10.24
Khuzestan	11	7	4	-9.71	-11.48	-10.24
Lorestan	24	7	4	-14.23	-11.48	-10.24
Bushehr	5	5	5	-27.88	-15.79	-15.79
Fars	15	5	5	-7.4	-15.79	-15.79
Kohgiluyeh and Boyer-Ahmad	21	5	5	-20.15	-15.79	-15.79
Hormozgan	27	5	5	-13.62	-15.79	-15.79

Notes: Table presents the intensity of the 2012 education quota across provinces, regions, and territories.
Source: Authors' calculation using university admission booklets and aggregate college students data reported by the Ministry of Science, Research, and Technology

Table J.2: Heterogeneous Effects on HSG Women's Employment and Wage

	LFP	Empl.	Unempl.	ln(Wage)
Panel A: by provincial intensity				
Treated × Intensity	0.001**	0.001**	-0.005*	0.0005**
	(0.001)	(0.000)	(0.003)	(0.0002)
R-squared	0.018	0.016	0.083	0.827
Panel B: by regional intensity				
Treated × Intensity	0.003***	0.002***	-0.006*	0.0005*
	(0.001)	(0.001)	(0.003)	(0.0003)
R-squared	0.019	0.016	0.083	0.832
Panel C: by territory intensity				
Treated × Intensity	0.002***	0.002**	-0.006*	0.0006**
	(0.001)	(0.001)	(0.003)	(0.0003)
R-squared	0.019	0.016	0.083	0.832
Observations	28,306	28,306	3,490	2,084

Notes: Table presents the heterogeneous effects of the 2012 Education quota on the labour market outcomes among young female HS/pre-university graduates by intensity. The dependent variables are labor force participation, employment rate, unemployment rate and wage rate. Wage rates (wage per hour) are log transformed and deflated by CPI which is equals 100 in year 2011. Heteroskedasticity-consistent standard errors accounting for clustering at the birth month-province level in parentheses. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
Source: Authors' estimations from Iranian Labor Force Survey (ILFS).

Online Appendix (not for publication): Model

In this online Appendix, we present more details of the model developed based on Card and Lemieux (2001). We assume that aggregate output in jobs for high school graduates at time t, y_t, depends on two CES subaggregates of female and male labor (L_t^f and L_t^m), and the technological efficiency (θ_t). Following the existing literature, we assume that the aggregate production function is also CES:

$$y_t = f(L_t^f, L_t^m; \theta_t) = [\theta_t^f (L_t^f)^\rho + \theta_t^m (L_t^m)^\rho]^{1/\rho}$$

in which

$$L_t^f = \left[\sum \alpha_c (L_{ct}^f)^\eta\right]^{1/\eta}$$

$$L_t^m = \left[\sum \beta_c (L_{ct}^m)^\eta\right]^{1/\eta}$$

where L_{ct}^f and L_{ct}^m are female and male labor of cohort c at time t. $-\infty < \eta \leq 1$ is a function of the partial elasticity of substitution between different cohort groups, σ_C ($\eta = 1 - 1/\sigma_C$). $-\infty < \rho \leq 1$ is a function of the partial elasticity of substitution between women and men, σ_S ($\rho = 1 - 1/\sigma_S$). α_c and β_c are relative efficiency parameters of female and male workers cohort c, respectively. We assume efficiency parameters are fixed over time. Firms' demand for different labors is determined where relative wages are equated to relative marginal products:

$$\frac{w_{ct}^f}{w_{ct}^m} = \frac{\frac{\partial y_t}{\partial L_t^f} \times \frac{\partial L_t^f}{\partial L_{ct}^f}}{\frac{\partial y_t}{\partial L_t^m} \times \frac{\partial L_t^m}{\partial L_{ct}^m}} = \frac{\theta_t^f (L_t^f)^{\rho-1} \Psi_t \times \alpha_c (L_{ct}^f)^{\eta-1} (L_t^f)^{1-\eta}}{\theta_t^m (L_t^m)^{\rho-1} \Psi_t \times \beta_c (L_{ct}^m)^{\eta-1} (L_t^m)^{1-\eta}} = \frac{\theta_t^f (L_t^f)^{\rho-\eta} \times \alpha_c (L_{ct}^f)^{\eta-1}}{\theta_t^m (L_t^m)^{\rho-\eta} \times \beta_c (L_{ct}^m)^{\eta-1}}$$

where $\Psi_t = [\theta_t^f (L_t^f)^\rho + \theta_t^m (L_t^m)^\rho]^{1/\rho - 1}$.

Thus, cohort specific wage gap of women and men HS workers in the year t is:

$$\log\left(\frac{w_{ct}^f}{w_{ct}^m}\right) = \log\left(\frac{\theta_t^f}{\theta_t^m}\right) + (\rho - \eta) log\left(\frac{L_t^f}{L_t^m}\right) + \log\left(\frac{\alpha_c}{\beta_c}\right) + (\eta - 1) log\left(\frac{L_{ct}^f}{L_{ct}^m}\right)$$

$$\Rightarrow \log\left(\frac{w_{ct}^f}{w_{ct}^m}\right) = \log\left(\frac{\theta_t^f}{\theta_t^m}\right) + \log\left(\frac{\alpha_c}{\beta_c}\right) + \left[\frac{1}{\sigma_C} - \frac{1}{\sigma_S}\right] log\left(\frac{L_t^f}{L_t^m}\right) - \left(\frac{1}{\sigma_C}\right) log\left(\frac{L_{ct}^f}{L_{ct}^m}\right) + e_{ct}$$