Are overly attractive government jobs distorting the labor market? Evidence from Bangladesh

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Abstract

Overly attractive government jobs may have implications on the labor market. This paper exploits an age ceiling policy that grants job aspirants eligibility for highly desirable public employment until their 30th birthday using population censuses and labor force surveys of Bangladesh for the period 1991–2017. Findings suggest that at age 30 the likelihood of private sector employment increases by about five percentage points, mainly driven by females in the later years of the sample period, after doubling the public service salaries. The increase in employment is explained by increasing labor force participation after expiration of the government job eligibility age rather than declining unemployment. A primary survey conducted online for this study shows that candidates queue for government jobs delaying other opportunities, and result in small monetary cost, substantial time cost, and forgone opportunities. On the other hand, there is indication of brain gain from public service exams preparation.

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1. Introduction

An overly attractive public sector may have consequences for the labor market. A public service premium may cause misallocation and productivity loss by diverting highly productive and innately entrepreneurial individuals from private to public sector (Cavalcanti & Santos, 2020). High wages in the public sector may also induce too many unemployed to queue for a job, thus increasing unemployment (Gomes, 2014). A premium can also affect human capital formation when selection into the public sector is competitive. Candidates might delay searching or taking up other employment opportunities in the hope of acquiring a government job by studying for selection exams or getting a required degree (Banerjee & Chiplunkar, 2020). Since most candidates will not get a job in the public sector, it is key to understand the direct and indirect costs incurred due to the preparation and the potential return on these investments in the private sector. If the costs are high or candidates forego more specialized education in favor of the minimal degree requirement, an overly attractive public sector may distort the labor market. On the contrary, if the preparation is highly useful in getting a job and valued in the private sector, a public sector premium may lead to a brain-gain that would not have occurred otherwise.[1] Empirical evidence on the effects of overly attractive public sector jobs is scant in the economics literature.

This study empirically investigates the impact of the public sector premium on employment in Bangladesh and explores the human capital implications of that premium using both secondary and primary data. Public employment is highly desirable in Bangladesh (M. Rahman & Al-Hasan, 2019).[2] The country's public service recruitment process imposes an age ceiling on eligibility, a common practice in many countries. The age ceiling might prompt aspirants to engage in government job preparation throughout the eligibility period, which would give rise to increased employment immediately thereafter. The upper age limit for eligibility for Bangladesh's public service has been 30 years for general candidates since 1991.[3] Exploiting that age ceiling policy, I examine the impact of becoming ineligible for overly attractive government jobs on employment. Data used for the empirical analysis are Bangladesh's population censuses and Labor Force Surveys (LFS) of various years between 1991 and 2017. An online primary survey conducted for this study through Facebook messenger enables a complementary investigation of the direct and opportunity costs of preparation for government jobs and its potential return. I sent 1500 questionnaires to individuals from five Facebook groups to cover the

[1] This is an equivalent concept of brain-gain by migrant-sending countries (Gibson & McKenzie, 2011).

[2] Public sector premium may prevail for many reasons including wage, pension, job security, scope for corruption, public service motivation (Rajibul & Kijima, 2021; Gindling et al., 2020; Islam & Hasan, 2020; M. Mahmud et al., 2020; Asseburg et al., 2019; Monem & Baniamin, 2017; Hanna & Wang, 2017; Mahuteau et al., 2017; Zafarullah & Siddiquee, 2001).

[3] There is a slight relaxation for a few select sectors (e.g., army) and groups (e.g., disabled, minority).

following target populations: those currently studying for government jobs, those who studied for government jobs in the past, and those who never studied for government jobs. Total 214 individuals responded to the survey which corresponds to an effective response rate of 57 percent, calculated over the number of individuals who had seen the message.

Regression discontinuity design (RDD) result shows a jump in employment at age 30: the likelihood of employment increases by about five percentage points once individuals become ineligible for government jobs. The employment effect occurs mainly in the female population and is particularly noticeable in 2015–16 and 2016–17, probably due to the fact that public sector pay was doubled in 2015. That discontinuity in employment is similar for both people with at least eight grade education and those without. The increase in employment at age 30 is explained by higher labor force participation rather than reduced unemployment.

Attributing the employment jump to becoming ineligible for public sector jobs requires that reported age is not manipulated and that there are no other policies affecting employment at age 30. Since the age reported in a given survey was not used to determine eligibility, the no manipulation assumption seems reasonable. Moreover, to the best of my knowledge, there are no other policies that also kick in at age 30 in Bangladesh. And in a robustness check, conditional expectations of education outcome given age do not show a discontinuity at age 30, which is reassuring. To address bunching at ages ending with zero and five, I evaluate the employment effect by dropping age 30, and the direction of the RDD result remains persistent. The result remains the same with geographical and year dummy controls. I also conducted a falsification exercise with data from the Indian state of West Bengal, which borders Bangladesh, speaks the same language, Bangla, and performs similarly in economic indicators. Since West Bengal did not apply a uniform ceiling on public recruitment eligibility at age 30 in the sample years, we would not expect a discontinuity in employment at this age; indeed, there is no evident discontinuity in the estimates. The magnitude of the employment jump in Bangladesh would have been more pronounced if it were possible to identify accurately the people who were well aware of the labor market situation and explicitly expressed their preferences. However, while most of the labor force is destined for informal sector employment, the available data cannot distinguish those who have applied for government jobs from those who have not, nor those interested in formal sector employment from those not interested. As a result, the effect of the public service premium appears small, although a discontinuous jump is evident at the eligibility age cutoff.

This study examines the effect of public service premium for different dimensions.

First, the RDD result support the argument that people queue for attractive public service Gomes (2014), yet, not by raising unemployment. Instead, this study unveils that queuing for government jobs stems from not participating in the labor market actively during the eligibility period for public service rather than increasing unemployment. This result harmonizes with observation in India that those who claim to be available for work may not actively looking for jobs in the private sector (Banerjee & Chiplunkar, 2020).

Second, the evidence from survey is consistent with the argument of Cavalcanti & Santos (2020) that overpaid public sector may affect occupational choice and cause misallocation by attracting high productive people to queue for government jobs, and crowding out private sector employment and entrepreneurship. About 15 to 19 percent of respondents reported they would have developed their own business if they were not studying for public service, and 30 percent reported developing own business as their alternative plan if they fail to secure a public service job. About 90 percent of responses by those who had prepared or were currently preparing indicated that they would have done other jobs, entered other business, or taken up other studies had they not been preparing for the public employment; about 70 percent of the responses of those currently preparing favor a plan for those alternative options after they reach the age cutoff without success. Furthermore, the evidence that students in the academic institutions preparing for government jobs indicates a possibility of compromising specialized education. 33 to 43 percent of those who currently studying for government jobs are engaged in full or part time study. However, this survey did not investigate willingness to compromise education and preparation in spare time. The evidences reinforce that overly attractive public service induces people to wait for a job that they will not get (Banerjee & Duflo, 2019), given the limited number of government jobs against long queue.

Third, this study provides new evidence of direct and indirect costs incurred from an exam based selection process in public service. The survey results show that direct or monetary cost is small and that time and opportunity cost of preparation for government jobs are substantial. Median total preparation spending is about double the monthly median income of the respondents. The median number of exam attempts is 13, and median hours spent is 1226 by a candidate during preparation for government jobs. Proxy indicators of the opportunity cost of time for government jobs—developing own entrepreneurship, taking up other jobs, and studying for academic course suggest considerable indirect cost. As response to reasons for not preparing, those who had never prepared for a government job also reported that the direct or monetary cost is not sizable, but the indirect cost is high.

Fourth, the study provides some evidence of human capital or brain gain from the preparation for public service exams. About 34 percent of the respondents who had prepared or are currently preparing reported finding the preparation 'very' or 'extremely' useful for other jobs; 39 percent reported finding it 'somewhat' useful; and about 27 percent finding it 'not at all' or 'not so' useful. To corroborate this perception, I also reviewed some exam materials and found that candidates generally study Bangla and English language and literature, general knowledge of Bangladesh and global affairs, mathematics and general science. However, the extent to which candidates mostly repeat content they have learned previously or skipped during their academic study, or acquired additional human capital is not clearly discernible from the survey or review. Candidates might gain trivial human capital against high cost; however, providing precise estimation of complex net human capital accumulation is beyond the scope of this study. The indication of human capital gain harmonizes with the brain gain from international migration (Bongers et al., 2021; Batista et al., 2007).

The allocation effect is perspicuous from delaying for overly attractive public service and deferring other opportunities. Occurrence of substantial cost is clearly discernible from the evidence; yet, concluding on net human capital accumulation, and whether attractive public service takes brain away or generates brain is subject to further research.[4]. The remainder of the paper is organized as follows. Section 2 briefly introduces the institutional and economic background of Bangladesh. Section 3 outlines the conceptual framework. Sources and descriptions of data are presented in section 4. Section 5 delineates the estimation approach. Section 6 describes the result. The final section presents conclusions and points to policy implications and directions for further work.

2. Institutional and economic background

About five to six percent of total employment and three to four percent of GDP in Bangladesh come from public administration and defense (MoF, 2016). Public sector is mostly formal sector in the labor market of Bangladesh. Small formal segment and large unprotected informal segment being a labor market feature, public sector job has been generally more desirable in Bangladesh, despite of its low pay in the past. The desirability for government jobs has many reasons along with stable wage benefits, including pension benefits, health and housing facilities, rare termination, public service motivation, scope for corruption, and social status. Public sector pay scale was revised to double in 2015 which may have contributed to the sector's attractiveness in the recent time. After that revision, the aspiration for the government jobs has become more visible, and we have been observing ongoing protests to revise labor market policies.

[4]The idea is also similar as brain gain and brain drain in international migration literature Docquier & Rapoport (2012); Gibson & McKenzie (2011); C. Cattaneo (2009)

Until a few years back, government sector had a quota system to show justice and honor to underprivileged and select groups of people. Under the quota system, about 55 percent of the public service recruitment came from distinct special groups—freedom fighters (30 percent), females (10 percent), district (10 percent), indigenous and minority (5 percent), with competitive selection accounting for the remaining 45 percent. Responding to a vast movement that demanded quota reform, the government abolished the quota system in 2018. Yet, more protests to raise the age ceiling for public service eligibility from 30 to 35 years are in action. This glimpse of the situation points out that the motivation for these movements may not have been only to ensure fairness and justice in the labor market but also to the high desirability of government jobs. Nevertheless, along with an illegitimacy concern of restricting eligibility at age 30, one argument for revising the age ceiling is that the private sector sets its preference silently, following the government standard. A snapshot of the demonstration is in Appendix 3, Figure A3.1.

Entry-level government jobs always have some age restriction with a few differences for some select people or professions in Bangladesh. In July 1991, the maximum eligibility age for public service recruitment was revised to 30 years from previous 27 years. With time economy has grown, and life expectancy of people has increased significantly. In 1991, life expectancy at birth were 56.5 for male and 55.7 for female, which in 2020 were 71.2 and 74.5, respectively (BBS, 2021). Ongoing demonstrations for raising the age ceiling to 35 present the increase in life expectancy as one of the arguments for revision demand.

Achievement of education has changed massively over the time, and the education curriculum and structure have also gone through changes and reforms in Bangladesh. According to UNESCO data, gross enrollment ratios in the secondary education in 2012 were 58.82 percent for females and 51.74 percent for males, which are 81.49 percent for females and 67.55 percent for males in 2020. Review of several recent statutory regulatory orders and government job vacancy announcements notifies that the lowest education for entry-level government jobs without experience is usually eight grades of education, excluding some exceptional flexible cases. Given the low education rate in the earlier years, the requirement for education might have been lower or unrestricted for some jobs.

About 85–90 percent of total employment in Bangladesh is in informal sector; the definition of the informal sector and employment varies.[5] Bangladesh's LFS 2016-17 considers informal sector as unregistered and/or small unincorporated private enterprises

[5]Studies in Brazil consider valid employment contracts as a distinction between formal and informal sectors, and they can be subcategorized further (Telles, 1993; Botelho & Ponczek, 2011).

engaged in production of goods or services for sale or barter and informal employment is the employment in informal sector (BBS, 2018). A division of the labor force into two or more segments, differences in working conditions attributed to differences in something other than workers' productivity, and mobility restrictions between segments can be considered features of the labor market segmentation (Cruz et al., 2019). The segmentation can be a cause or consequence of market forces, voluntary and involuntary informal employment, and primary and secondary labor market.[6] Informality of employment in Bangladesh can be a cause or consequence of the labor market segmentation. Public sector jobs with wages rationed above the equilibrium can be considered the primary labor market. When sheer part of the labor force is destined for informal secondary market where wage is flexible and responds to excess demand conditions, a dedicated attempt for the primary public sector job appears a rational labor market response of the job seekers.

Youth unemployment rate in Bangladesh has been a concern for a long which is even higher among the educated youth (R. I. Rahman, 2014). Definition of employment and unemployment changes over time.[7] Since a large part of the economy is informal, the definition is sometimes ambiguous and subject to the framing of employment question and the respondent's understanding of work. While Bangladesh has no unemployment benefit or support mechanism, unemployed people rely on their family income or business for survival, or live in dire poverty. Note that people live below the upper poverty line (lower poverty line) in Bangladesh is 24.3 (12.9) percent in 2016, 31.5 (17.5) percent in 2010, 40.0 (25.1) percent in 2005, 48.9 (34.3) percent in 2000, and 50.1 (35.2) percent in 1995-96, according to government statistics. The lower poverty line is based on food poverty and upper poverty line on both food and non-food (BBS, 2019).

3. Conceptual framework

In framing the concept of the problem, we can think of two broad segments in the labor market—a small government sector (g) and a large non-government sector (p). Jobs in public sector are mostly formal; non-government sector has a small formal part, but large part is informal. Public sector jobs have wage and pension security, health and housing access, the slightest fear of termination, and higher social status. The formal segment of the private sector is competitive, and wages and other benefits are not guaranteed. The informal part of the private sector is all your own, and no security and support mechanism available.

People can earn their livelihood by working in one or more of the labor market seg-

[6](García, 2017; Günther & Launov, 2012; Leontaridi, 1998; Demekas, 1990)

[7](Table A4.1 in Appendix 4, for definition over the period)

ments. In the presence of better opportunities in public sector, people may find comparative advantage in public employment. Those who cannot manage to get into the public sector turn in formal private sector, and those who are not absorbed in the formal public or private sector are destined for informal private sector. There are also people who estimate their potential above return from public employment, or cannot afford the cost of delaying other opportunities, or are indifferent of employment sectors.

People can decide whether to do the government or non-government job until they are 30 years old. Because of the age ceiling policy, government jobs no longer exist in the job decision set after age 30, remaining options are non-government employment and entrepreneurship. Therefore, job seekers have to decide whether their preference is government jobs, prepare for the particular type of exam, and achieve one by age 30. They analyze their labors' lifetime cost and benefit in the decision process. The analysis considers all premiums of the government job over the non-government if they succeed (b_s), the probability of success (p), direct and indirect costs of the preparation (c), and use of human capital gain from the preparation for other jobs if they fail (h_f). A rational individual is expected to try for a government job and defer taking up other options until age eligibility expires if $p(b_s) + (1 - p)(h_f) \geq c$.

Due to overly attractive public sector, the labor market may encounter two consequences. First, allocation effect derived from the self-selected labor supply decision; and second, subsequent human capital accumulation effect. Allocation of labor can take different forms: misallocation of innately entrepreneurs from entrepreneurship to public service; misallocation of specialized workers from specialized fields to the general administrative government jobs; keeping ready workers away from work or encouraging taking up below-potential jobs; enriching public service with productive individuals to produce public goods efficiently. Subsequent human capital investment decisions can redesign human capital accumulation: impairment by compromising specialized academic education for public service; impediment by depleting the knowledge that gained before preparation; retain the same level by revising and replenishing only existing knowledge stock; accumulation by studying for the public service recruitment exam that can be valuable for private sector after failing to secure a government job; accumulation by studying for the exam that can make the public servant more productive when recruited.

This study sheds light on some dimensions of channels of public service premium effect in the labor market. I particularly examine the allocation effect as to whether employment increases immediately after being ineligible for public service, whether people delay taking up other opportunities, and whether there is opportunity options for the time spent for the public service preparation. The human capital accumulation channel mainly investigates whether there is substantial cost of preparation, whether people find the preparation useful for non-government jobs, and whether the materials candidates study during the preparation for government jobs against cost incurred augment or deplete existing human capital stock.

4. Data

4.1. Population censuses and labor force surveys

Population census is good microdata for employment status and individual- and household-level information, although detailed information is not available there. Bangladesh conducted censuses in the years 1974, 1981, 1991, 2001, and 2011. Bangladesh has recently finished census 2021 but the microdata is not yet available to use for research. I use population censuses from 1991 onwards, and in 1991, government revised the age ceiling from 27 to 30 years as an eligibility criterion in public service recruitment process. Census 1991 was conducted in March 1991 and age ceiling was revised in July of the same year, which makes result of this year subject to argument. It is possible that people interested in public service were aware of upcoming revision, so 1991 census can be treated as after policy revision year. It is also possible that government job aspirants did not know anything about the upcoming revision, in that case 1991 census would be considered as pre-revision data. The census data earlier than 1991 is not available and Bangladesh had gone through economic and political transformations in the early 1990s. Hence, using data 1991 onward makes good sense although it would be nice to have pre-period of age revision data. Bangladesh conducts LFSs generally in three to five years of interval; as an experiment, LFSs 2015–16 and 2016–17 were conducted quarterly. In LFS, there is detailed information about the working-age population. I use LFSs for the years 2002–03, 2005–06, 2010, 2013, 2015–16, and 2016–17. The combination of LFSs with censuses of 10 years intervals gives a good continuity of data for the years from 2001.

Bangladesh's statistical agency, Bangladesh Bureau of Statistics (BBS) produces the data used for empirical estimation of this study. Census data is collected from IPUMS international (IPUMS, 2020). Publicly available census data contain 10 percent observations of 1991 and 2001 censuses, and five percent observations of 2011 census. The information was collected through direct interviews with everyone who spent the survey night in Bangladesh. 1991 and 2001 sample censuses are systematic samples of every 10th dwelling with a random start, drawn by IPUMS. 2011 sample census is a systematic sample of every 10th dwelling with a random start, drawn by BBS.

LFS 2002–03 was conducted in a short period of time, so it is advised not to strictly compare with the later LFSs. LFS 2005–06 is a stratified cluster sample design that utilized the population census 2001 as the sampling frame. The estimate is reliably obtainable at rural, urban, statistical metropolitan area, and district level in this survey (BBS, 2008). LFS 2010 developed its master sampling frame using the 2001 census enumeration area as the sampling frame. The estimates can be derived at division level (BBS, 2011). LFS 2013 is representative at division level with rural, urban, and city corporation breakdown, and gender disaggregation (BBS, 2015). Quarterly LFSs (QLFS) 2015–16 was the first attempt of quarterly LFS in Bangladesh. The QLFS is representative at division level with rural, urban, and city corporation breakdown (BBS, 2017). QLFS 2016–17 was a similar approach to QLFS 2015–16 (BBS, 2018). Because every survey methodology and coverage is different from others, comparing surveys might not be the right approach. Therefore, instead of strictly comparing censuses and surveys, I have used them together and also each year separately for the estimation. Table A4.1 in Appendix 4 contains detailed information about LFSs and censuses, and employment status variable.

LFS 2002–03 data set does not have sample weight, so I assign a uniform weight to all observations that gives the survey an equivalent weight of census 2001. Censuses for 1991 and 2001 have 10 percent, and census for 2011 has 5 percent observations of the population. QLFSs provide weight for both quarterly and annually; I use annual weights to be consistent with other censuses and surveys. I use probability weight in both pooled and each year estimation, so the estimate can be interpreted as for the entire population of working age. Total observations between age 15 and 60 are 5431078 in census 1991, 7044983 in census 2001, 108192 in LFS 2003-03, 107500 in LFS 2005-06, 115247 in LFS 2010, 4320681 in census 2011, 97342 in LFS 2013, 310841 in QLFS 2015-16 and 305090 in QLFS 2016-17.

4.2. Primary sample survey through messenger

I conduct a sample survey through the Facebook messenger to have a better understanding of the findings from the censuses and LFSs, and implications for labor market. Implicit objective in designing the survey questionnaire and frame is to understand cost and gain of preparation for government jobs. Target population in the survey are those who are currently preparing for government jobs, those who prepared in the past, and those who never prepared. Facebook groups are selected based on their objectives and on observations of their activities. The groups have objectives of sharing knowledge for people who are currently preparing for government jobs, career expositions and updates for currently student, and on the job issues for government employees. After pretesting and piloting the questionnaire, I sent questionnaires to about 1500 individuals on Facebook messenger as direct message. Individuals chosen from five Facebook groups were recently active in the groups. I received 241 responses against total sent 1500 questionnaires and 214 individuals answered at least one question. After cleaning the data, total usable observation is 208. The coarse response rate is only 16%, that is the number of response calculated over number of questionnaire sent. However, the effective response rate is above 50%, that is, when the response rate is calculated over the number of people who have actually seen the message with attached questionnaire. Total male respondents is 181 and female 28. Although effective response rate in female (53%) is equivalent to male (56%), share of female response is low. This is because I could send questionnaire to fewer number of female, perhaps due to less education and social media activeness among them. Collected information are broadly on individual's characteristics, monetary and time cost, opportunity cost of time of preparation for, and perceptions of government jobs. Number of response is different for each question since respondents were allowed to decide whether to answer or skip for every question. The detail procedure of conducting the survey is in Appendix 4 (4.2).

Characteristics of the respondents. Total number of response is for sex 205, age 206, education 199, current situation 161, and monthly income 111. Female respondent is 14 percent and male 85 percent. Share of female response is low probably because of their low participation in higher education, labor force, and social media. About 97 percent of the respondents are of age up to 40 years as expected, since the target group in the survey is the people who are interested in government jobs and social media user. Seven percent of currently studying for government jobs respondent reported their age between 31-35, the response is reasonable even though ceiling for government job is age 30. This is because if someone apply for government job by age 30, they can participate in exams in cases when the exams take place after their age 30, so during this time they may keep studying. There are also a small select group of people who enjoy flexible age ceiling up to age 32. About 61 percent of the respondents have bachelor or master degree. About 79 percent of the responded who are currently studying and 92 percent of the respondents who studied before for government jobs have bachelor or master degree. 71 percent of those who said that they will study for government jobs in the future are of with education 12 grade or undergrad, probably, they are currently studying for their academic degree. 51 percent of them who are not interested in government jobs have education less than bachelor. Education and study status for government jobs indicate that educated people in the labor market are inclined to government jobs. A quarter of individuals who are currently studying for government jobs already have a full-time government job, probably they are aspiring for a better one. About 63 percent have a full-time government job and about 22 percent have a full-time non-government jobs in them who studied for government jobs before. Appendix 4.2 Table A4.5 presents the descriptive statistics of the respondents by their status—currently studying, studied before, will study in the future, and never studied for government jobs.

Income is higher for them who studied for government jobs before than them who are currently studying, because those who studied before are mostly of age above 30 and employed. The median income of them who are currently studying is Tk. 7500 and who studied before is Tk. 35000. Income distribution of them who will study is similar to who is studying and who never study is similar to who studied before. Standard deviation is bigger for studying and will study group than the other groups compared to their mean value. Mean(sd) income are for currently studying people Tk. 13038(15415), studied before Tk. 39233(29121), will study Tk. 14875(28184) and never study Tk. 34818(29838). Mean income(sd) are for full-time government employee Tk.37991(16681), full-time not-government formal employee Tk. 35039(30880), Own business of any type Tk. 22250(13443). Appendix 4.2 Figure A4. displays cumulative distribution of monthly income for the groups who are currently studying for government jobs and who studied before.

Job preference of the aspirants includes 24 percent any government job, 17 percent any BCS job, 12 percent public bank job, 11 percent autonomous public institution, 9 percent NSI job, 7 percent any teaching job, 7 percent auditor, 5 percent computer operator, 4 percent office assistant, 4 percent other (Appendix 4.2 Table A4.6).

5. Empirical framework and estimation

One of the empirical objectives of this paper is to estimate the causal impact of being ineligible for lucrative government jobs on total employment. In doing so, I compare employment status of working age people who are eligible for government jobs and who are not. The hypothesis is that if government jobs are more beneficial people may wait for achieving one before becoming ineligible, and after losing the eligibility they may rush up for other employment opportunities that may cause employment jumps up. There is an age-restricted job application policy for public service that makes job aspirants ineligible to apply for government jobs after their 30th birth date. I exploit this policy variation of age at 30, an identification strategy that can be considered a regression discontinuity design in the current setting.

The age ceiling was revised from 27 year to 30 year in 1991. It would be good had it been possible to compare the employment status of people for 30 year and below with above 30 year for the pre- and post-revision period from comparable datasets. BBS officials inform me of the unavailability of census and labor force data for periods earlier than 1991. On the other hand, even if we had data for years before 1991, comparing pre- and post- period around 1991 might not have given much meaningful estimate considering the lack of targeted data for the current purpose and also that all the changes have happened in the labor market and economy of the country during this period. Another approach could be comparing employment status of people, otherwise equivalent, who prefer (applied for) government job with who do not prefer (did not apply for) government job. To do so, assigning treatment in a random experiment that make willing individuals eligible for government job against the control group willing but not eligible, and not willing probably would be most acceptable method. Random experiment by the researcher is not a feasible option in this case, only option available is exploiting the observational data to apply quasi random method. From the available data, it is not possible to distinguish the people who prefer government jobs from them who do not or who applied for government job from them who did not, but we know broadly who are eligible to apply for a government job and who are not based on the age ceiling condition. Taking all the limitations and facts into account, I find RDD is a plausible identification strategy for explaining the causal relation between employment and unobserved highly-desired government jobs using age 30 as cutoff over the period since 1991 onward.

The age restriction policy features the two ingredients of a RDD design in the data–one is observable covariate, age and another is the cutoff that determines assignment to treatment, age 30. If outcome, likelihood of employment, shows a discontinuity at the cutoff we might reasonably interpret it as the effect of public service premium. However, there are concerning issues when apply RDD in this case. I use entire sample of the labor force surveys and population censuses, so at age 30 there may have other issues that can contaminate the RD estimate. I cannot specify individual with their job preference, and the small select group of people, e.g., freedom fighters' offspring, who enjoy age flexibility up to 32 years old. Besides age ceiling general condition, there are other requirements by job type, e.g., education. It is not possible to identify which particular jobs require what other eligibility along with age restriction, so disaggregated or sub-group analysis by job type eligibility is not a feasible option. In addition, because the age variable is discrete, usual RDD with bandwidth near the cutoff is not an option. Estimating aggregate effect at age 30 cutoff from the entire sample seems best possible way, however, I will be cautious about the estimation, interpretation of the results, and provide enough justification and falsification.

Following the conventional RD setting (Rubin, 1974; Angrist & Pischke, 2008; Dong, 2015), the regression specification is

$$Y_i = \beta_0 + \beta_1 T + f(Age_i - 30) + \epsilon_i ....(1)$$

To estimate the average treatment effect at age 30, $E[Y_1 - Y_0|Age = 30]$, data observation is $Y = (1-T)Y_0 + T(Y_1)$ since we cannot observe simultaneously Y_0 and Y_1. The continuity and smoothness assumptions allow to estimate the discontinuity at the cutoff due to treatment using non-parametric or semi-parametric procedure based on a local randomization around the cutoff considering that $lim_{x_{i\downarrow} x_o} E(Y_i|age_i = x)$-$lim_{x_{i\uparrow} x_o} E(Y_i|age_i = x)$, particularly for the large sample (Hahn et al., 2001; Kane, 2003; Angrist & Pischke, 2008; M. D. Cattaneo et al., 2018). Because the score variable in this study age is discrete, I cannot estimate the effect using local randomization due to mass points and non-existence of observations close to cutoff. Instead, I rely on polynomial function of $f(Age_i - 30)$ for the entire age window of labor force and extrapolate at age 30.

Because of the discreteness of running variable, the estimation is done at age level, $Y_{ij} = \beta_0 + \beta_1 T(1[Age > 30]) + f(Age_j - 30)^k + \epsilon_{ij}$
$f(.)$ is the spline of age function.

I use the following model specifications upto 3^{rd} order polinomial

$$Y_{ij} = \beta_0 + \beta_1 T + \gamma_k \sum_{k=1}^{3} (Age_j - 30)^k + \epsilon_{ij}$$

$$T = \begin{cases} 1 & \text{Individual i's age j} > 30 \\ 0 & \text{Individual i's age j} \leq 30 \end{cases}$$

Y_{ij} is the outcome variable, individual i's employment status at age j. T stands for the indicator function $I[.]$ of treatment ($T = I[Age_i > 30]$). The dependent variable is defined as

$$Y_{ij} = \begin{cases} 1 & \text{the individual i is employed at given age j} \\ 0 & \text{otherwise (unemployed, does household work, does not work)} \end{cases}$$

β_1 potentially captures the employment effect of switching from being eligible for public service to not being eligible; that is, β_1 can be interpreted as the effect of public service jobs premium on employment at age 30.

Non-linearity of the counterfactual conditional mean function, non-smoothness of running variable age at 30, and other unobservable factors related to age that might cause jump of employment at age 30 may lead to bias estimate. The conventional approach of RDD to address the non-linearity is to estimate the average effect in a small neighborhood of the cutoff point so that correct model specification does not remain a big concern. Local linear or quadratic polynomial or other smooth functions are recommended than using global high-order polynomials (Gelman & Imbens, 2019). Zooming in around the cutoff requires measures in general to deal with loosing observations and small sample bias; discrete nature of running variable with small number of bin makes it more difficult to zoom in around the cut off and select bandwidth. Having small number of mass points, continuity-based analysis that fit a local linear polynomial within mean squared error (MSE) optimal bandwidth is not appropriate (Calonico et al., 2017; M. D. Cattaneo et al., 2018). Since discrete nature of score variable make it impossible to compare outcomes for observations just above and just below the treatment threshold, we need to choose functional form for the relationship between the treatment variable and the outcomes of interest (Lee & Card, 2008).

To the best of my knowledge, no other policy on age restriction prevails in Bangladesh to cause outcome to be different age 30. I have checked if any social security programs are designed targeting age 30, but found none (GED, 2015). Figure A2.1 in Appendix 2 reconfirms this showing no abrupt change in the graph at age 30 in education outcome regression. Although only the cubic specification (Table A2.1 in Appendix 2) shows a little positive change, Figure A2.1 does not show any visible discontinuity at age 30. Education is an important factor for formal jobs, therefore, not much real concern remains about continuity at age 30.

One identification concern is how much randomness is there in age, that is, whether people can predict birth date in connection to government job or manipulate birth date in reporting. Predicting birth date does not seem an issue at all given the level of parent's lack of awareness and unpredictability of jobs vacancy announcement. However, age reporting can be an identification threat for some reasons including partial and faulty coverage of birth registration. There is no reason to think that people may manipulate their age systematically when respond to survey and census questions keeping in mind the eligibility of government jobs because there is no link between government jobs and surveys. However, age is rounded to year in the data and maybe there is incoherence between how people report age culturally and how government jobs age ceiling rule is defined. Therefore, it is worthwhile to discuss age reporting concern a little detailed.

There are a few concerns of misreporting of age data—age heaping at years ending with 5 or 0, digit preference, age exaggeration, age understatement (Singh et al., 2021; Jowett & Li, 1992; Bhat, 1990; S. Mahmud & Becker, 1984; Bairagi et al., 1982; Edmonston & Bairagi, 1981). Although not a great deal, overtime reporting pattern shows some improvement (Singh et al., 2021). The data confirms (Panel A, Figure 1.1) that people over-report their age that ends with 0 and 5. There are two issue to consider about individual's reporting of age at 30—what they perceive by age 30 and how much they misreport. In a typical understanding of age counting, people may report their age as 30 years old when actual birth date is between 30th and 31st. In the same stream, some censuses and surveys instruct to put, for example, 00 if age is below one year or 12 months (Appendix Table A4.2). On the other side, the recruitment circular and the common understanding of 30 years in Bangladesh is the age before 30th birthday. In the government jobs vacancy announcement, it is usually mentioned that the age should not be above 30. For instance, The statutory regulatory order framed the age ceiling policy as 'no person shall be eligible to appear at the examination if he/she is less than 21 years of age or has exceeded 25 (later revised to 27 and 30) years of age on the first day of the month in which the commission invites applications for holding the examination'. Newspaper report the 30 year age ceiling which is actually before 30th birth day (Appendix 3 Figure A3.1 Panel B). To reconfirm, I asked some public service employees and candidates about the actual birth date of age ceiling restriction and they informed it is up to 30th birth date. In this set of understanding, people may report age 30 when they are at before 30th birth date. Therefore there is a chance that 29 years old people who is before their 30th birthday report their age as 30. Those who are 29 and report as 30 do not create any problem in the estimation since they are still eligible for the public service job under age eligibility rule. After their 30th birthday and before 31st birthday people may report their age as 31 since people tend to exaggerate age, in such case there is not problem either. Nonetheless, those who passed their 30th may introduce measurement error in the estimate if they report their age as 30 since there is chance of overreporting 0 and 5. For identification with discontinuity, I use cutoff at age 30 as up to 30th birthday for eligibility of public service candidacy. Study suggests evidence of avoidance of number ending with 1, 4 and 9 in age reporting (Singh et al., 2021). If this is true and those who are 31 but report as 30 could lead to bias estimate. To address the misreporting of age, besides the benchmark estimation, as a robustness check, I estimate by dropping observations in the age bins 30 and 31.

In global extrapolation, quadratic and cubic polynomials do not show much noticeable difference in the data. I estimate OLS regressions of age window 15–50 years for linear and 15–60 for quadratic and cubic splines to address non-linearity. I plot the average employment by age bin in diagrams along with regression estimate to make non-linearity issue clearly visible. I have adjusted for the weights of LFS in every regression estimation. As an experiment, before adjusting pooled weight, the estimated coefficients from individual-level estimates are equivalent to those of the estimate using the count of observations in each age cell. Because of the assigned weight, only pooled estimates vary slightly, but individual year estimates remain the same. I have experimented several times with different sample sizes, age group, the definition of variables, etc. and decided to stick to the age group of the working age population before retirement age in the government sector, i.e. 15 to 60 years old.

6. Results

6.1 Regression discontinuity results

This section presents regression discontinuity results. Quadratic and cubic specifications fit average value better for the entire age window 15–60. Linear specification fits only with a smaller age window after age 30. Therefore, I present linear results with quadratic and cubic only in the pooled figures and tables, and skip linear specification in all other figures and tables. First, I present the main regression results in tables—Table 1, Table 2 and Table 3; then, the corresponding graphical evidence in figures—Figure 1.1 Panel B, Figure 1.2, Figure 2, and Figure 3. Supplementary results are Appendix 1 in Table A1.1–A1.6 and Figure A1.1. Appendix 2 presents falsification, robustness and validation check in Tables A2.1–A2.6 and Figures A2.1, A2.4.1, A2.4.2, and A2.5.

Turn to interpretation of the regression results. Table 1 presents the estimated employment effect of being ineligible for government jobs from the pooled data during the period 1991–2017. Columns 1, 2, and 3 in the table are respectively linear, quadratic, and cubic specifications; results of all the specifications are similar in terms of magnitude and significance with a little exception for male. Panel A exhibits all working age individuals, Panel B only males, and Panel C only females. The likelihood of employment for all individuals increases by four to five percentage points at one percent level of significance in three types of specifications at age 30. The likelihood of employment[confidence interval] increase is in linear specification 0.045[.020 .069], quadratic 0.036[.010 .062], and cubic 0.051[.025 .077]. There is no significant difference of male employment at age 30, only cubic specification is slightly positive at five percent level of significance. The difference in employment is mainly explained by female work force, increase is between 0.042 and 0.047 in three specifications, at one percent level of significance. Average mean employment at age 30 with respect to specification varies between 50 and 52 percent, for male between 89 and 94 percent, and for female between 15 and 17 percent. Overall, average female employment is very low and male employment is quite high which may have affected their response to the age ceiling policy.

Employment response of age ceiling recruitment policy in government jobs seems different for male and female population. Table 2 presents the regression results of each year for males only, and Table 3 females only. There is no increase in male employment after age 30 at one percent significance level over the entire period 1991–2017. Some years show a little increase at five percent significance level in cubic specification only—0.010 in 1991, 0.012 in 2011, 0.058 in 2013, 0.022 in 2015-16. Only 2010 employment increases in both quadratic (0.041) and cubic (0.048) specifications at five percent significance. There is insignificant decrease in some years. In all the years between 1991–2017 average male employment at age 30 is between 84 and 97 percent. Average male employment at age 30 is already high, so there is little scope to drive the increase up at turning age 31. Therefore, male employment is not much responsive to the age ceiling at the extensive margin of being employed or not criteria. In female population, main increase in employment outcome after age 30 is in later years, mainly in 2015-16 and 2016-17. In earlier years there are a little increase although with some insignificant decrease too. In the earlier years, the mean employment of female at age 30 was extremely low, e.g., six percent in 1991. This negligible share of female employment cannot actually drives the change of employment due to the age ceiling. However, the female mean employment at age 30 has increased persistently over the period to reach up to 29 percent in 2016-17. With the increasing share of female employment at age 30, the increase of employment turning to age 31 also has become more visible. Besides women's increasing education and labor force participation, the try and wait for government employment might also be a reaction to the increasing pay that pay scale was revised to double in 2015 in the government jobs.

Histogram of discrete variable age in Panel A in Figure 1.1 shows the age-heaping tendency in reporting the age end with 0 and 5. Panel B of corresponding Table 1 plots the linear, quadratic, and cubic splines with the age bin mean of employment rate for the pooled data during 1991–2017. The solid vertical line is the age cutoff in the estimation, and the vertical dash lines are to mark the age–heaping in the data generation process at ages end with 0 and 5. Cubic specification seems to fit the age cell mean better, though quadratic and cubic prediction fits are very close to each other. Panel B of Figure 1.1 shows the evidence that employment increases abruptly once individuals become ineligible for public service jobs. As expected, when individuals become ineligible for government jobs, they become serious about grabbing other employment opportunities whatever they can manage. The concerning spike in the age histogram at age end with 0 and 5 at Panel A do not seem to be disrupting of the employment rate at Panel B. Figure 1.2 presents the linear, quadratic and cubic fits of male and female group at Panel A and Panel B that correspond Panel B and Panel C respectively of Table 1. Similar as seen in the regression, there is clear jump at age 30 for female at Panel B but not much for male at Panel A. Figure 2 and Figure 3 present the regression results of corresponding Table 2 and Table 3 for each year separately for male and female population. For male population, graphs are pretty smooth over the entire period except a few years like 2010, 2013. For female in Figure 3, clear jump is visible at years 2015-16, 2016-17 and also slightly in other years like 2010, 2013. Following the 2015 pay scale revision, public sector job has become more attractive (Islam & Hasan, 2020; M. Rahman & Al-Hasan, 2019).

Appendix 1 presents some supplementary results of subgroup estimates. The main results interpreted above is for all sort of people. Nevertheless, education is an important determinant of formal jobs, control for education in the main estimation is difficult because education data provided in category and the categories are not same for each sample year. Therefore, Table A1.1 presents the pooled estimate for male and female by two education group in Panel A–D. There is no noteworthy difference between individuals with education at least eight grade and less than eight grade for both male and female. Corresponding Figure A1.1 of Table A1.1 visually represents the result. Table A1.2 and Table A1.3 present regression results of of each year during 1991–2017 for all individuals and individuals with at least 8 grade of education respectively. Similar result is obtained for individuals with a minimum of eight grades education (Table A1.3) and for all individuals (Table A1.2). The result is that the likelihood of employment increases equivalent percentage point with respect to years and specifications. Table A1.4 and Table A1.5 present results for male and female group with at least 8 grades of education for each year separately. Table A1.1–A1.5 and Figure A1.1 reinforce the result obtained in the main part of the paper. Also, from labor force effect over non-labor force, and employment effect over unemployment, it is observed that increase in employment after eligibility for public service jobs stems mainly from increasing labor force participation rather than declining unemployment (Table A1.6).

Appendix 2 presents some robustness, and falsification exercises. Table A2.1 presents the pooled result if age impacts the individual's education across all the years of the chosen age group for individuals with at least eight grads of education (Panel A) and individuals with education above 5 grade (Panel B). As expected and seen in Figure A2.1, other than cubic specification, age is not a determining factor of education at age 30, i.e., no abrupt discontinuity of age at 30. Cubic specifications seems significant, particularly for the individuals above five grades of education, however, there is no abrupt change or discontinuity at this age compared to the other points. Given that education is important indicator of formal jobs, if people intentionally manipulate age that should be reflected in education continuity which is not true. Therefore, we may safely rely on the discontinuity of employment at age turning 31 in the main result.

As a robustness check at intensive margin, I estimate the age effect on work hour of the employed men and women. The results in Table A2.2 and Table A2.3 show that there is no significant difference in work hour at age ≤ 30 and above except a few cases of declining work hours. Work hour would be discontinuous if people work less hour to prepare for government jobs. Nonetheless, how many hour an employed people work does not solely depends on employee unless there is opportunity to choose work hour or part-time work while part-time work culture is not well established in Bangladesh. Therefore, we do not see an age ceiling effect in intensive margin in terms of work hour. Rather, this indifference of work hour at age 30 justify the continuity of age and the finding of jump at age 30 in employment is due to the age ceiling policy that restrict eligibility for government jobs at age 30.

I present the result by dropping age 30 in Table A2.4 and Figures A2.4.1 and A2.4.2. The likelihood of increase in employment remain positive at turning age 31 but no longer at one percent but five percent significance level. To check robustness, I also drop public service holder from survey data for the period 2003–2017 since this information is available only in the survey, but not in census. I estimate the employment effect by excluding individuals who are employed in the government sector. This estimation is to check if the increase in employment after age 30 comes from the recruitment in government. The result remain same as the main result (Table A2.5). I also check robustness by controlling for geographic variables like division and rural-urban and using year dummy (Table A2.6). There is no reason for the employment to be much different at turning age 31 due to geography and accordingly result remain unchanged. Therefore, We can reasonably conclude that employ is likely to increase at age turning to 31 due to the age ceiling policy.

India has similar age restriction policy for public service jobs. However, the age ceiling is not so much uniform like Bangladesh, rather it has various age ceiling targeting many groups. But there is no restriction at age 30 in the sample years; the ceiling starts way above age 30. West Bengal state of India borders Bangladesh in the western side, speaks same language, Bangla, and performs equivalently in economic terms. Since there is no restriction at age 30, we would not expect an employment jump at this age; and indeed, there is no jump at age 30. Figure A2.5 shows no noteworthy difference in employment at age 30, as expected.

6.2 Results of the primary sample survey

I intend to understand the RDD results that the prevalence of more beneficial government jobs affects labor market decision, and to dig into channels of potential consequence from primary observations. When government jobs offer better compensation compared to other jobs, lingering over the preparation for government jobs during eligibility period might be rational response for an individual, which can introduce different types of cost and inadvertent gain. Cost can emanate from time spent on preparation, not exploiting or utilizing other potential opportunities, and monetary costs etc. In contrast, human capital accumulation can happen from studying for government jobs.

Data from survey confirms that people repeatedly try for government jobs until they get one even though other opportunities are available. Out of 208 responses, 41 percent currently studying for government job exams, 19 percent studied before but not longer, 24 percent will study in the future, and 16 percent never studied before and will not study for government job. A good number of respondents who are currently studying for government jobs took exam before. Some of the respondents have become successful in achieving a full-time jobs, but they are still studying for government job. 72 percent (n=46) of the currently studying respondents took government exams before and 28 percent (n=18) are attempting for the first time. 31 percent (n=22) have ever secured a full-time job of any type (government, non-government) and 69 (n=50) never got a full-time job. Half of the respondents (n=7) who are currently studying and have ever secured a full-time job (n=15), secured the job even before they start for government job preparation. Candidates of government jobs attend multiple exams generally and keep trying until they achieve one or become ineligible. Those who are currently trying for the job already attended 19 (n=41,sd=19) exams on average. Those who attended before but no longer attended 18 (n=31, sd=20) exams on average. Those who are planning to attend exams in the near future think on average they need 9 (n=37, sd=8) attempts. It seems respondents who are yet to begin their journey of obtaining a government job race underestimate cost of preparing for such exams and overestimate their capability.

Cost of preparation for government jobs, particularly in terms of time is substantial. Figure 5 present cumulative distribution of total money (Panel A) and time (Panel B) spent for those who are currently studying and who studied before for government jobs. Who prepared for government jobs before spent on average Taka 97584 (sd.153702) and who have been preparing already spent on average Taka 106824 (sd.170929) over their entire preparation. To understand the magnitude of the money distribution, it can be noted that median income of Bangladesh is about Taka 141400 ($1414)[8]. Who prepared for government jobs before spent total 2361 (2882) hours on average (sd) for their entire preparation. Those who have been preparing for government jobs have already spent total 2354 (2985) hours. If we consider full-time work as 8 hour a day, this numbers means

[8]2022 income, Source: https://worldpopulationreview.com/country-rankings/median-income-by-country (accessed on 11 September 2022)

around 295 days. This is a huge time for aggregate economy considering that most youthful age group of the workforce spend the time. If the time is conducive to build human capital then this may be a human capital gain from government jobs preparation and vice versa. Median spent money is Tk. 34375 and time is 1226 hour.

Cost of waiting and preparing for government jobs is difficult to measure without precise data or experiments. However, besides direct cost like money and time above, I attempt to make an inference of the opportunity cost from information on potential opportunities people give up for the sake of probable government jobs. Figure 6 frames indicators to resemble the opportunity cost of time for preparation of government job in this study. Panel A presents what people perceive would do if they were not studying for government jobs. About 90 percent of the responses of the currently studying for government jobs or studied before are that they would take up other job, study, develop own business, help in family business etc. with this time had they not been studying for government jobs. This clearly indicates opportunity cost of preparation for government jobs. Panel B presents what people plan to do after expiring age of eligibility if they fail to secure one government job. People who are currently studying for government jobs report their career plan after they expire the government job age ceiling without success. 30 percent plan is for developing own business, 29 percent for further study or work, and 30 percent do not know what they will do. These information are clear indication of opportunity cost of delaying for government jobs. To perceive the use of the preparation beyond government jobs, Figure 7 presents respondents' self reported perception about the usefulness of government jobs. The distribution of response to a five-point scale from "Extremely useful" to "Not at all useful" looks pretty symmetric in both side. 39 percent response favors the middle point "Somewhat useful" for both group—studying currently and studied before. Preparation usefulness in the first point of left side 'very useful' is 18 percent response from currently studying and 36 percent who studied before. In the right first point 'Not so useful' is about 21 percent by who studying and 9 percent by who studied before. The furthest left 'Extremely useful' response is 11.5 percent by who studying and 3 percent who studied before. In the farthest right, 'Not at all useful' is about 10 percent response who studying and 12 percent who studied before. So very or extreme useful responses are 30 and 39 percent, somewhat useful 39 percent, and not so or not at all useful 31 and 21 percent for two groups who studying currently and studied before. Those who never studied or will not study for government jobs also reveal the cost of preparation in Figure 8. The reason why they never try for government jobs include response of 25 percent already got preferred job, 31 percent low chance of getting government job, 38 percent indirect cost high and 6 percent direct cost high. We can deduce that due to the indirect cost including time, giving up opportunities, low probability of getting government jobs, there is substantial cost incurred for overly attractive government jobs.

6.3 Discussion on the results

The empirical results above conform with the hypothesis that in segmented labor market, people prefer more beneficial segment and keep trying and waiting to achieve a job in that segment. As a result, we see employment jump up just after passing the eligibility age for public service jobs. The result is analogous to the findings of other studies. In the book "Good Economics for Hard Times" by Banerjee & Duflo (2019), 'Waiting for Forever' section refers to a collaboration Banerjee made with a training and job placement business in the service sector in India. The data confirmed the company's worry that they were not doing particularly well at placing their students. 450 persons completed a course out of 538 young men and women who signed up for that. Among them 179 persons were offered the job while only 99 of them accepted the offers. After six months only 58 were in the jobs the company had found for them, a hit rate of just over 10 percent. Another 12 were working elsewhere. The researchers asked a group of those who were offered a job but never accept it or quit more or less immediately what they were doing instead. They were either taking competitive exams to get a government job or a quasi-governmental organization, e.g., a public-sector bank or studying to complete the bachelor degree and then apply for a government job. Or, they were just sitting at home, even though their families could ill-afford that. Something similar prevails in other countries (Banerjee & Duflo, 2019). We can interpret the results as a distortion effect of public service job premium on employment.

The likelihood of total employment to jump up at age 30 indicates that people wait for the public service jobs and defer other employment opportunities. The survey data reconfirms the empirical result that people try repeatedly for public service jobs. The empirical result is mainly explained by female labor market agent while the survey result is mainly by the male; notwithstanding, the mechanism is same. LFS and population census cover large sample population where male response may not precisely reflective in extensive margin of binary employed and not-employed status given that male are the main bread winner in cultural setting. On the other hand, online survey data mainly cover male population because of survey setting. During the waiting time for public service jobs the candidates incur substantial costs of money and time, particularly the time cost is prominent (Figure 5). The opportunity cost of time for the preparation of government jobs is visible in Figure 6. While the economy has to incur cost to build human capital, the monetary, time, and other indicative opportunity costs above do not tell us enough about the human capital net loss or gain through the preparation cost of government jobs. I set out to explain the implications of time cost on economy though human capital. Overly attractive public service can affect human capital and the economy through one or multiple channels.

Misallocation of human resources between public and private sector through selection channel can take place as a consequence of public service job premiums. For example, a student of engineering department may opt for administrative public service job; an individual with innate entrepreneurial capacity may not go to explore opportunities and excel in own caliber. In figure (6), Panel A survey question asks what would they do with the time had they not been studying for government jobs and the response rate for developing own business are 19 (currently studying) and 15 (studied before) percent; Panel B asks what is their plan afterwards if they do not succeed in achieving a government job and the response for developing own business is 30 percent. On top of that, entrepreneurial standout cannot be judged in a simplistic way because taking challenge and doing rather than studying hone this prowess. Large part of the response also is that they would have taken up other jobs had they not been studying for government jobs. Public service premiums may encourage to wait for cozy government jobs instead of taking entrepreneurial challenges and other potential jobs.

Overly attractive public service jobs can affect human capital accumulation. Aspirants of public service jobs due to high premium may compromise with their knowledge and expertise from primary source, e.g., academic study. For example, a full-time student in educational institution may release academic study time for the public service jobs preparation. Such diversion can have medium to long term effect on human capital formation. In the survey, currently studying for government jobs is 33 percent of them whose current status is full-time study (n=40), and 43 percent of them whose current status is study and part-time work (n=26). Accumulation or depletion of human capital can happen during preparation. The preparation materials can garner human capital that can be useful beyond the government jobs; the perception of the public service aspirants partially support this. About half of the respondents find the preparation for government job useful for other jobs or professions in the labor market.

To understand the use of preparation for government job for other job, I review the preparation materials of some selective exams arranged by Bangladesh Public Service Commission (BPSC) (Table A3.1 in appendix 3). Most educated people prefer Bangladesh Civil Service (BCS) job (Table A4.6). In government jobs hierarchy, BCS is the top cadre job although there are categories within BCS jobs. BPSC is the responsible agency to manage BCS and some other exams. Sometimes based on BCS cadre exam score, candidates are passed on to non-cadre job instead of arranging non-cadre job exams separately all the time. Hence, first I briefly review the exam structure and study materials of BCS job, and then slightly touch on a few other exams. Broadly the aspirants study Bangla & English (language & literature), general knowledge (Bangladesh & international), and basic science (math, computer, environment, etc.). The exam structure and study materials are similar for non-cadre job too, main difference probably is level of difficulty. Not much practical learning or training is garnered in the syllabus and required in the exam. In the standard academic study up to higher secondary (HSC/12 grade) level all these basic materials are covered; specifically, Bangla is the native language and medium of study up to HSC, English is taught simultaneously with Bangla from the beginning of education and mostly a medium of study at the university. In the undergrad and master level, student learn intermediate to advanced level of their major subject and basic to intermediate level of the minor subjects. From the contents of the exam syllabus, it is difficult to conclude whether they only recap and review the earlier acquired knowledge or learn new things and gain new skills; whether they lose the useful knowledge during preparation that they have already gained; whether they could get other jobs and gain equivalent or more human capital from on the job training. The preparation against the cost incurred for the preparation of government jobs can be replenishment of earlier academic gain, or makeup of lacking from compromise of academic study, or attainment of new knowledge to enrich human capital, or replacing earlier learning with new learning.

The loss and gain of the preparation for government jobs depend on the difference between opportunity they lose and net human capital addition to their stock from depletion and replenishment in terms of human capital measures. If there is net gain of the preparation, after the eligibility for public service this can have productive use for the economy and vice versa. I find evidence of misallocation of talent, that is, human capital accumulation is affected quite strongly as evidenced by the time spent studying for the exams. However, whether the time is spent wisely or not is only indicative but not decisive from the data. An intuitive understanding on the channels of human capital gain and loss of preparation is the interest than drawing a conclusion. Future research can draw conclusion on the the loss and gain of allocation of human resources.

7. Conclusion

Government jobs in Bangladesh are highly coveted for a number of reasons besides wages, for example, pension benefit and job security. This study examined the effect of high desirability of government jobs on employment and human resource accumulation in Bangladesh. Findings suggest that premium or over attractiveness of government jobs in a government vs. non-government sector segmented labor market have a distortionary effect. In the presence of attractive government jobs, people are likely to delay searching and taking up other opportunities, try repeatedly for public sector jobs until they become ineligible, and incur substantial costs due to the preparation.

Exploiting an age ceiling policy, the RDD finding suggests that the likelihood of employment increases by about five percentage points for people who expires the eligibility age for government jobs. Employment increases mainly for females and considerably after doubling the public service pay in 2015. Increase in employment is derived from increasing labor force participation rather than declining unemployment. Survey data suggests that during eligibility period, people attends multiple public recruitment exams, incurs small direct monetary but substantial time and opportunity costs. People's perception of usefulness of preparation in obtaining other jobs and review of exam materials do not provide definitive answers on human capital accumulation; but, it appears to indicate limited human capital gain against high cost incurred. Further research is needed to conclude on net human capital accumulation from segmented labor market.

Prevalence of premiums in public service seems to have adverse impact on the economy. To ward off negative consequences of such premiums, Banerjee & Duflo (2019) recommend measures other than cutting government job wages since that action would probably invite strong opposition. Several easy approaches recommended include limiting the number of times an individual may apply for government jobs, and making the age cutoff more stringent. Similar measures with required modifications can be adopted in Bangladesh in the short run. Particularly restricting number of times a candidate can attend exams would be a better approach than current uniform age ceiling at age 30 considering other factors like unequal number of years in the universities for graduation, discrimination against older candidates. Achieving optimum wages and other benefits for the entire labor market in the long run with no public vs. private segmentation might be more sustainable and efficient approach. In doing so, further research would need to evaluate public service efficiency margin due to the premiums, and net human capital gain as a result of preparation.

This study examined only the supply side of the labor market. The results do not completely apply to cases where employment is affected significantly on the demand side, i.e., where job creation or overall employment opportunities is insufficient. Nevertheless, the demand side of the labor market can also be affected by public service premiums; disproportionately attractive government jobs may discourage labor market agents from proactively taking on entrepreneurial roles and generating employment.

The research approach applied in this study can be extended beyond public sector jobs in Bangladesh to any segmented labor market scenario. Many countries, including India, have similar labor market features, and different types of segmentation. Further study can estimate the magnitude of employment effect precisely by identifying individuals who prefer public service compared to who do not. This study explored a research scope of brain gain through preparation for government jobs, further study can take the issue up to estimate the extent of net human capital gain.

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Results: Tables and Figures

Empirical results

Table 1: Effect of job entry age-ceiling policy on employment, 1991–2017

	Dependent variable: Employment status (0/1)		
	Panel A: All		
Age>30	0.045***	0.036***	0.051***
	(0.012)	(0.013)	(0.013)
Mean at age 30	0.520***	0.510***	0.503***
	(0.010)	(0.010)	(0.006)
Observations	16,300,207	17,840,954	17,840,954
	Panel B: Male		
Age>30	-0.014	-0.007	0.021**
	(0.021)	(0.012)	(0.009)
Mean at age 30	0.942***	0.909***	0.893***
	(0.021)	(0.012)	(0.008)
Observations	8,117,362	8,960,245	8,960,245
	Panel C: Female		
Age>30	0.042***	0.047***	0.046***
	(0.013)	(0.012)	(0.014)
Mean at age 30	0.170***	0.158***	0.160***
	(0.008)	(0.005)	(0.007)
Observations	8,182,845	8,880,709	8,880,709
Age group	15-50	15-60	15-60
Spline	Linear	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the group age between 15 and 60, and all education. Panel A presents all individuals, Panel B Male and Panel C Female. Pooled dataset consists of population census 1991, population census 2001, LFS 2002-03, LFS 2005-06, LFS 2010, population census 2011, LFS 2013, QLFS 2015-16, QLFS 2016-17. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table 2: Effect of job entry age-ceiling policy on employment 1991–2017 by year, male

	Dependent Variable: Employment status (0/1)					
	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	-0.001	0.010**	0.019	0.018	-0.008	-0.011
	(0.005)	(0.004)	(0.019)	(0.015)	(0.021)	(0.021)
Mean at age 30	0.948***	0.942***	0.838***	0.845***	0.886***	0.880***
	(0.005)	(0.002)	(0.019)	(0.014)	(0.016)	(0.016)
Observations	2,762,521	2,762,521	3,564,726	3,564,726	54,720	54,720
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.050	0.037	0.041**	0.048**	-0.006	0.012**
	(0.040)	(0.022)	(0.018)	(0.019)	(0.006)	(0.005)
Mean at age 30	0.915***	0.841***	0.848***	0.844***	0.939***	0.935***
	(0.039)	(0.021)	(0.014)	(0.013)	(0.005)	(0.004)
Observations	54,383	54,383	57,331	57,331	2,119,383	2,119,383
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	-0.035	0.058**	-0.011	0.022**	-0.007	0.007
	(0.042)	(0.028)	(0.011)	(0.009)	(0.009)	(0.014)
Mean at age 30	0.970***	0.902***	0.916***	0.908***	0.908***	0.916***
	(0.0406)	(0.0269)	(0.008)	(0.004)	(0.006)	(0.007)
Observations	47,705	47,705	151,448	151,448	148,028	148,028
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the male population group age between 15 and 60, and all education. Each year separately presented in Panel: A–I. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

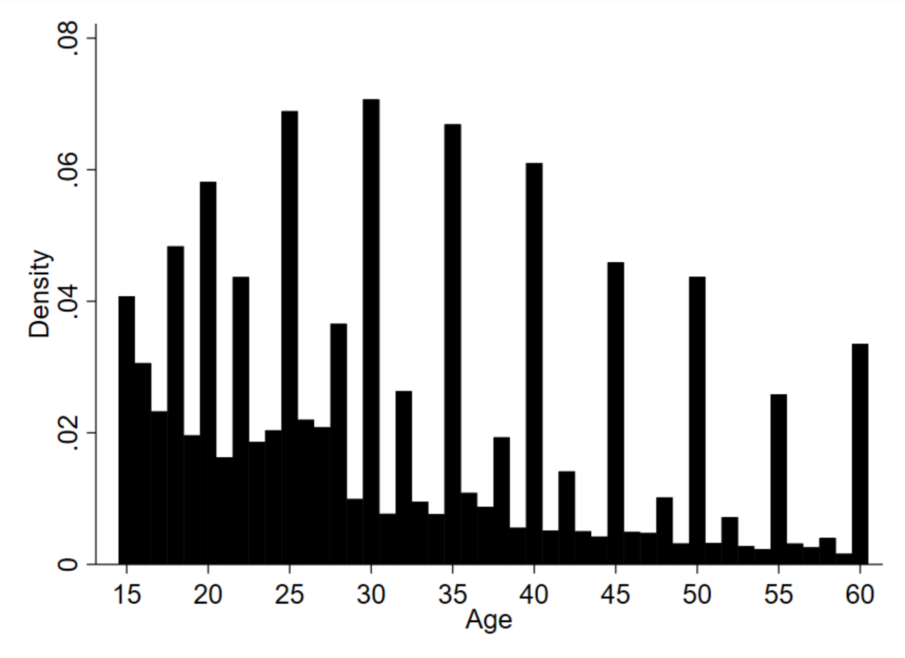
Table 3: Effect of job entry age-ceiling policy on employment 1991–2017 by year, female

	Dependent Variable: Employment status (0/1)					
	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	0.001	-0.002	0.013**	0.015***	0.022*	-0.012
	(0.002)	(0.003)	(0.006)	(0.005)	(0.011)	(0.014)
Mean at age 30	0.062***	0.061***	0.110***	0.112***	0.140***	0.161***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.010)	(0.013)
Observations	2,668,557	2,668,557	3,480,257	3,480,257	53,472	53,472
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.008	0.011	0.095***	0.021	0.004	-0.002
	(0.013)	(0.019)	(0.031)	(0.037)	(0.004)	(0.004)
Mean at age 30	0.127***	0.102***	0.138***	0.158***	0.093***	0.099***
	(0.013)	(0.019)	(0.015)	(0.013)	(0.004)	(0.002)
Observations	53,117	53,117	57,916	57,916	2,201,298	2,201,298
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	0.056	0.062	0.024**	0.039***	0.059***	0.057***
	(0.045)	(0.054)	(0.010)	(0.009)	(0.012)	(0.015)
Mean at age 30	0.173***	0.179***	0.247***	0.243***	0.290***	0.289***
	(0.019)	(0.014)	(0.007)	(0.004)	(0.006)	(0.005)
Observations	49,637	49,637	159,393	159,393	157,062	157,062
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

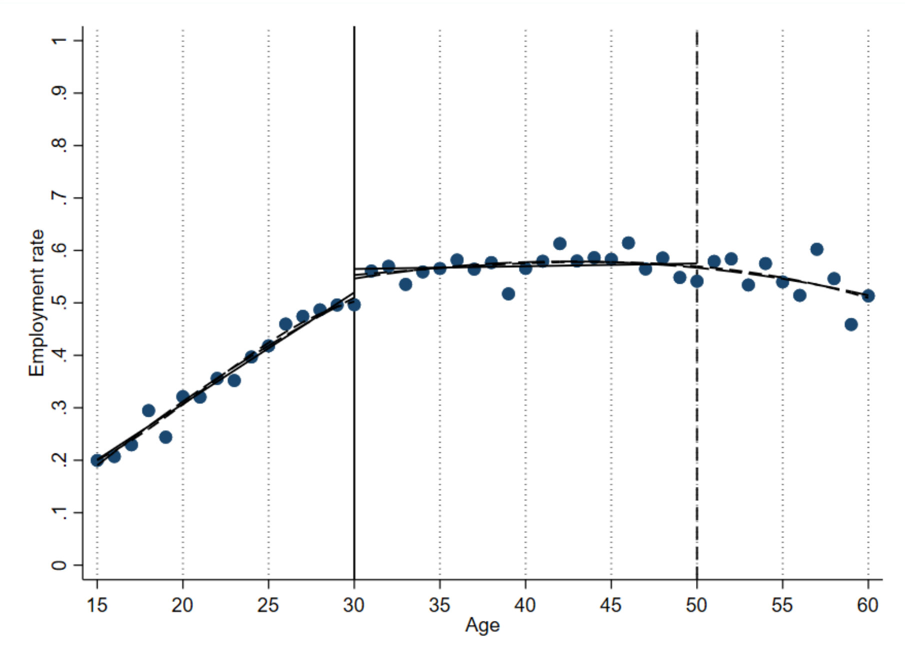
Notes: OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the female population group age between 15 and 60, and all education. Each year separately presented in Panel: A–I. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Figure 1.1: Age histogram and estimates of turning 31 years old on employment for all age and sex group together, 1991–2017 pooled

Panel A: Histogram of discrete age variable



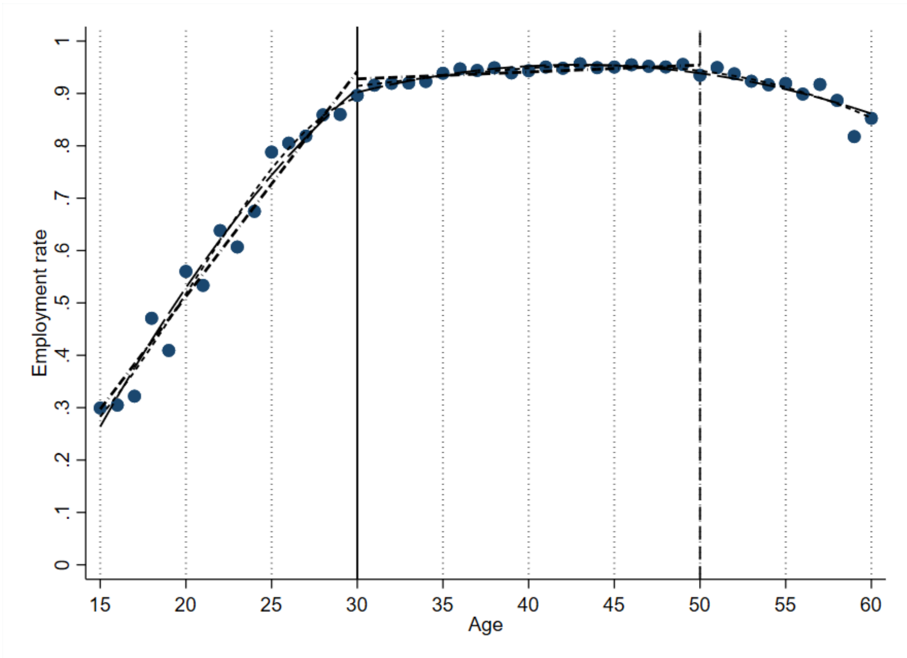
Panel B: Aggregate effect of turning 31 years old on employment



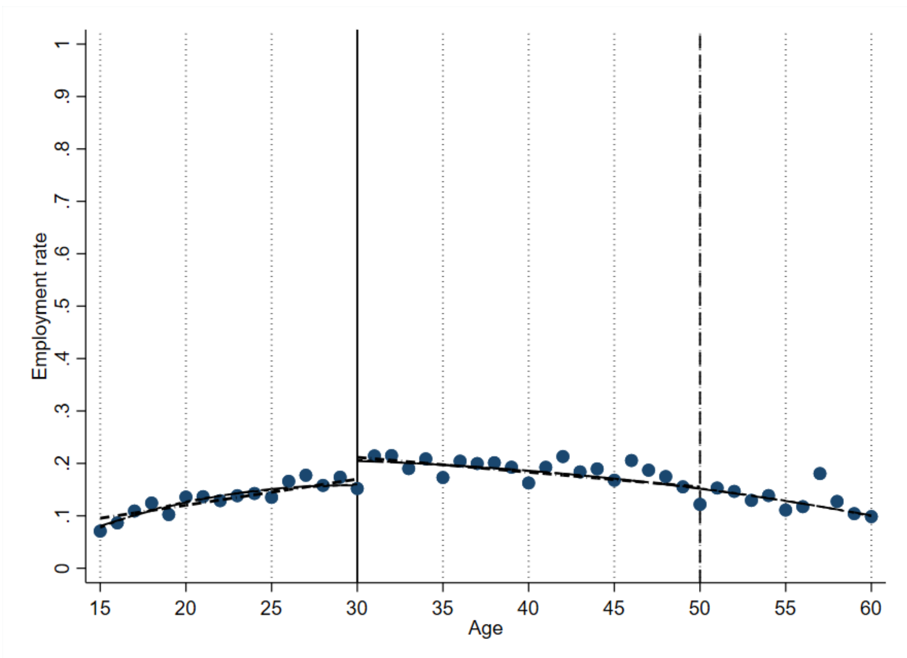
Notes: Panel B corresponds the Panel A of regression Table 1.

Figure 1.2: Employment rate by sex, 1991–2017

Panel A: Employment rate of male

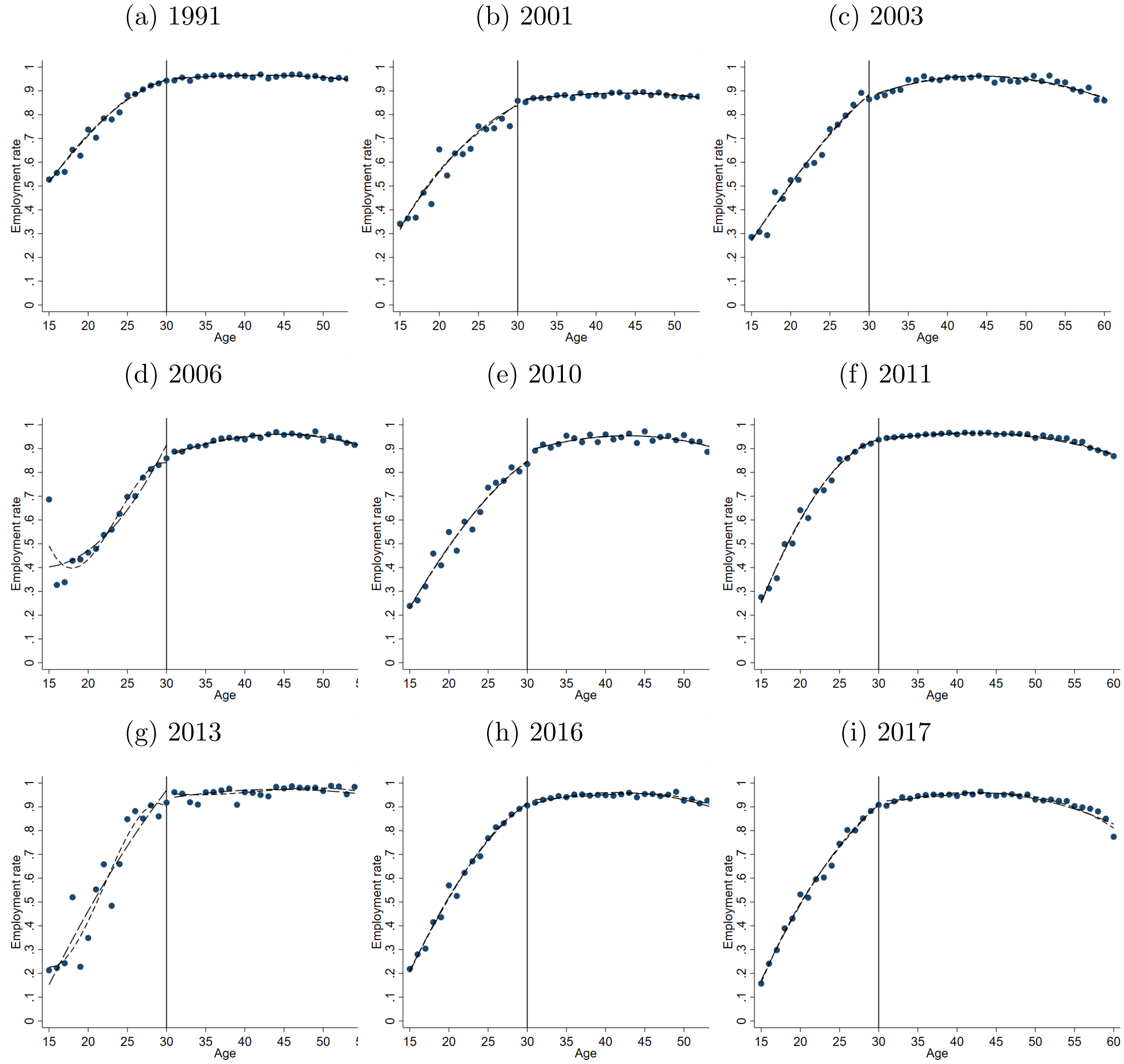


Panel B: Employment rate of female



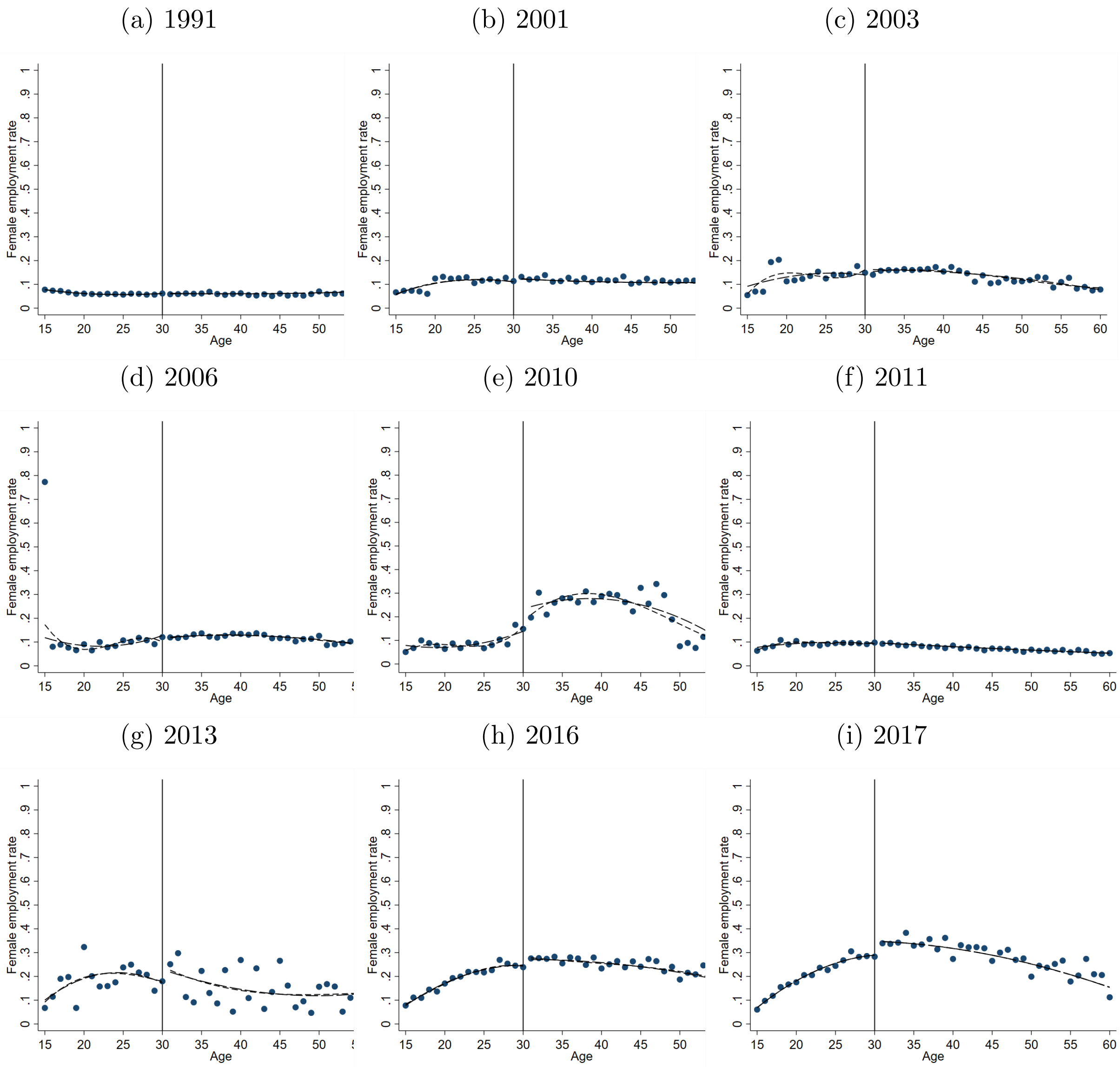
Notes: Panel A and Panel B correspond the regression Panel B and Panel C respectively of Table 1.

Figure 2: Employment rate of male by age, 1991–2017



Notes: Figure 2 corresponds the regression Table 2.

Figure 3: Employment rate of female by age, 1991–2017

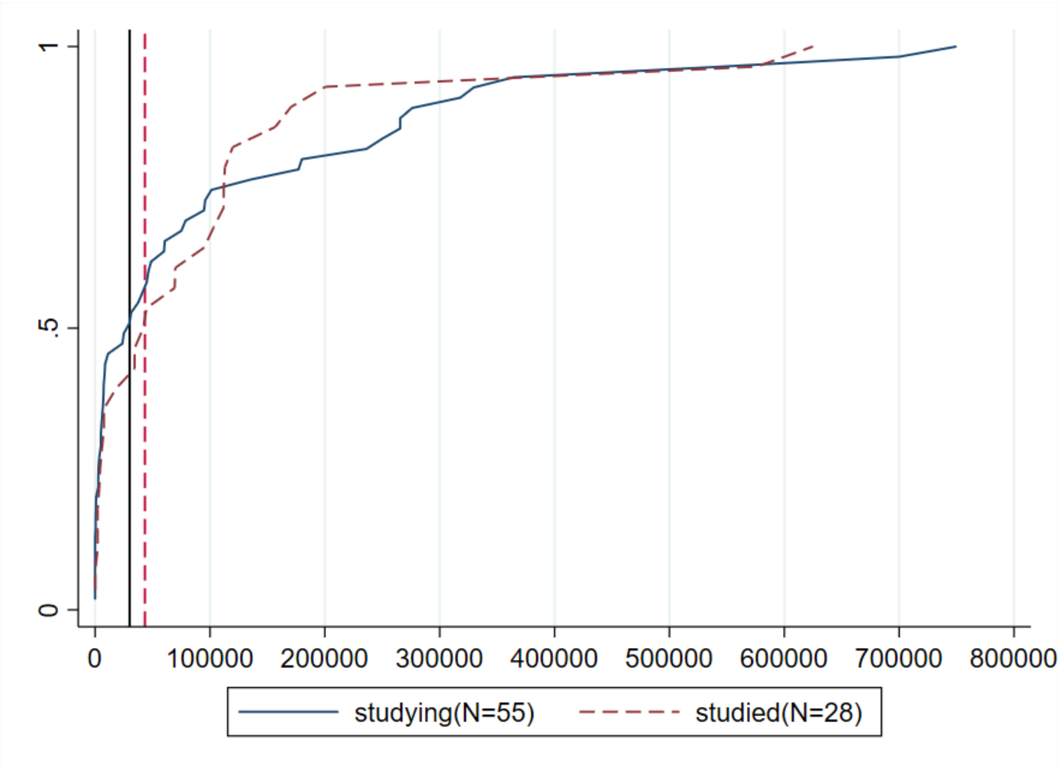


Notes: Figure 3 corresponds the regression Table 3.

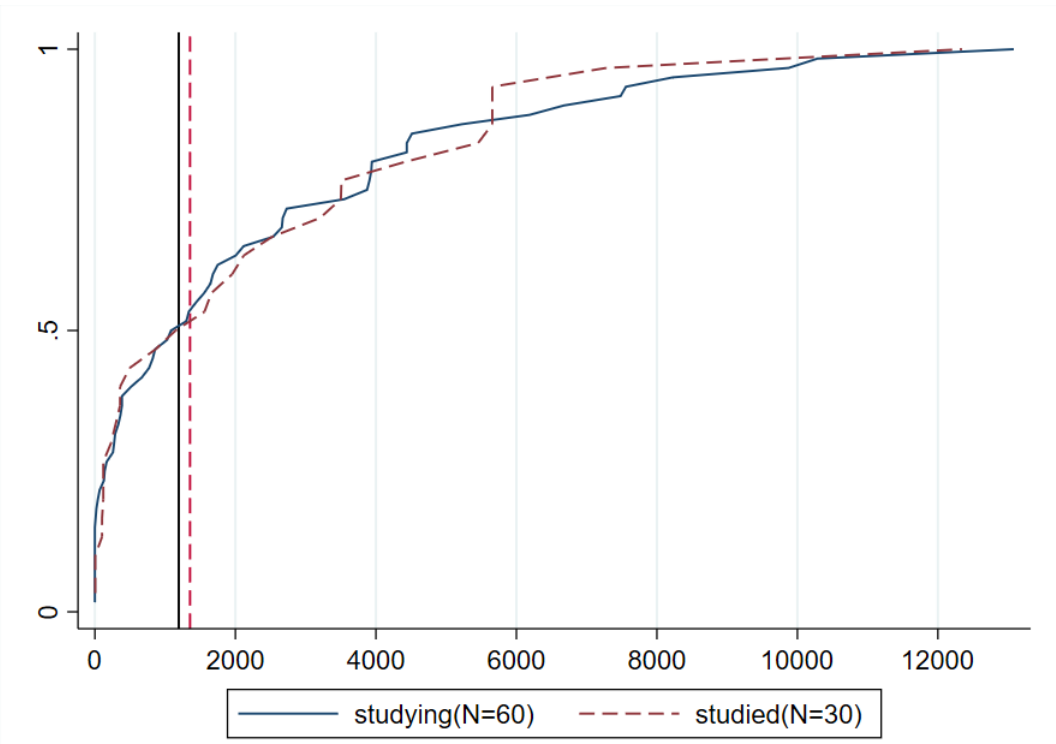
Survey results

Figure 5: Monetary and time cost of preparation for government jobs, by study status

Panel A: Cumulative distribution of total money spent(Taka)



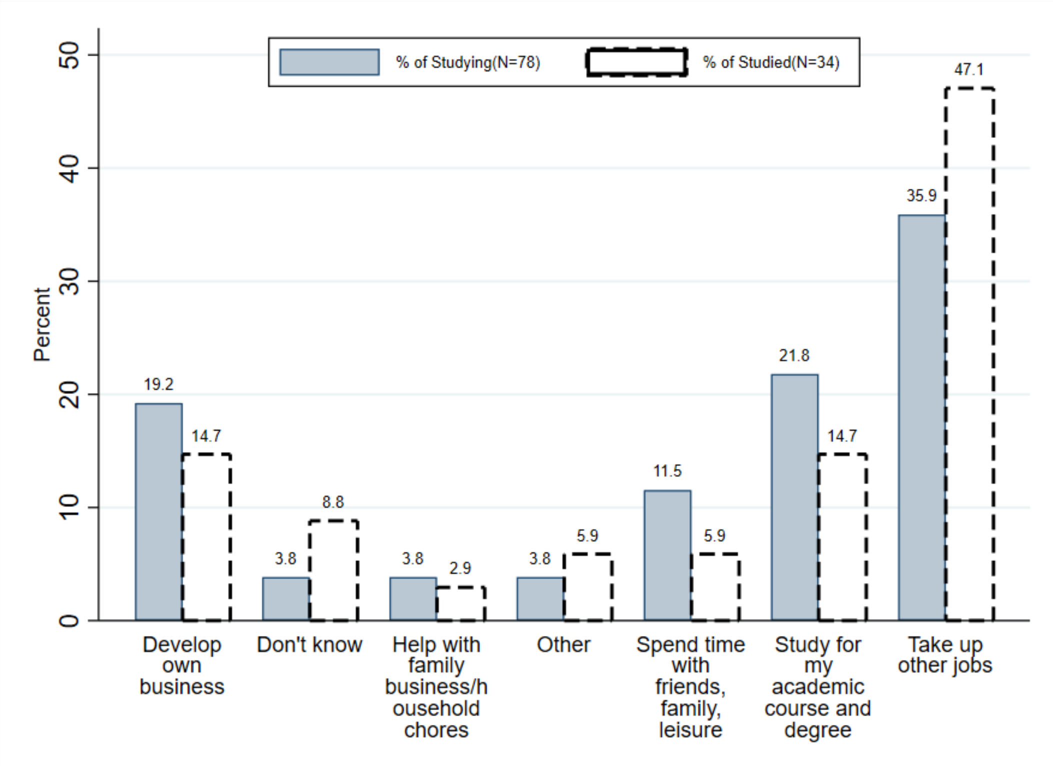
Panel B: Cumulative distribution of total time spent(Hour)



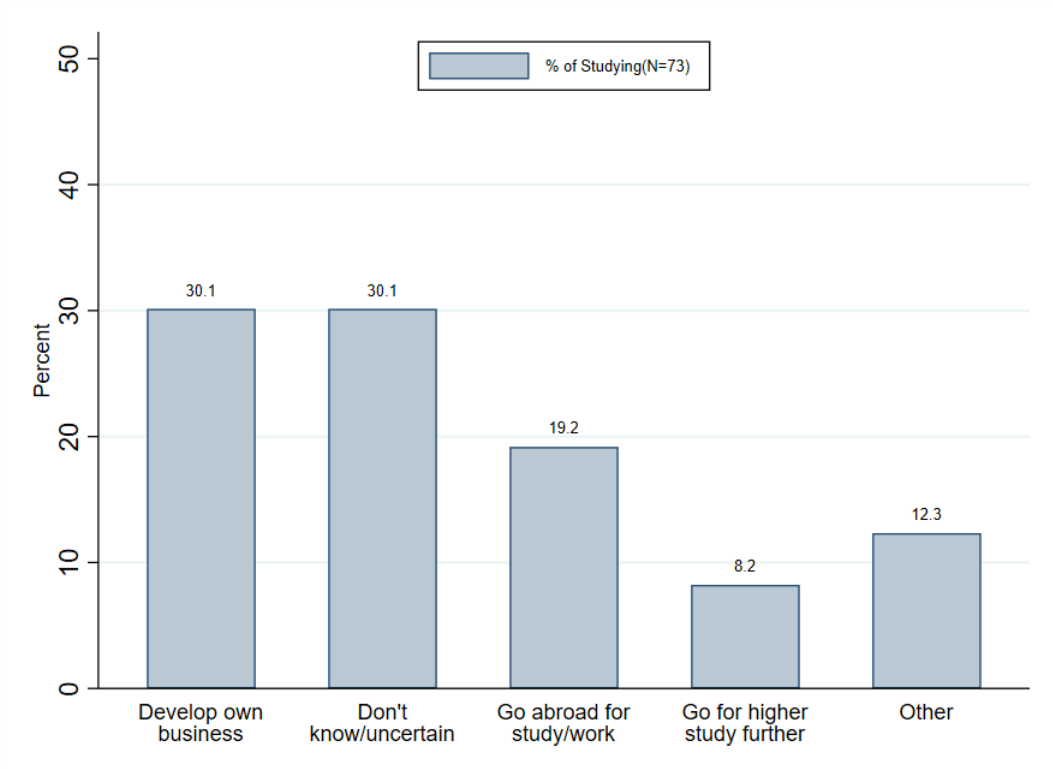
Note: Vertical lines are median values

Figure 6: Proxy indicators for opportunity costs of preparation for government jobs

Panel A: If you had not been studying for government job exams, what would you have done with your time instead? (Please choose all options that apply)

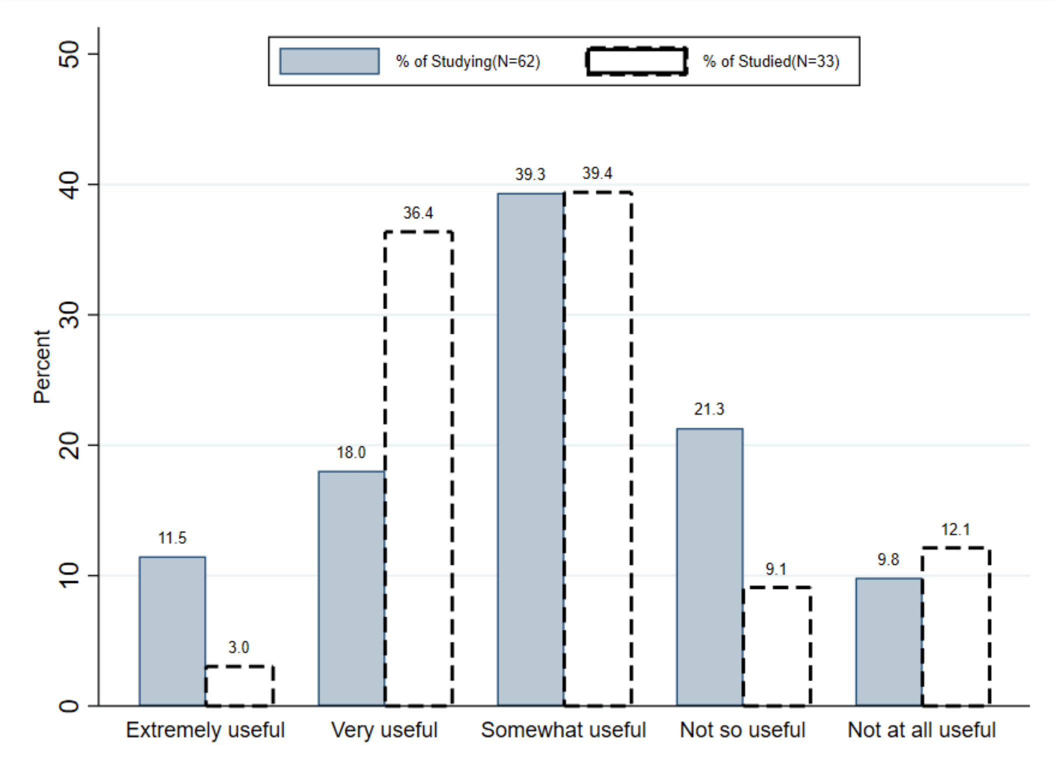


Panel B: In case you cannot get one government job before reaching age ceiling, what would you plan to do later? (Please choose all options that apply)



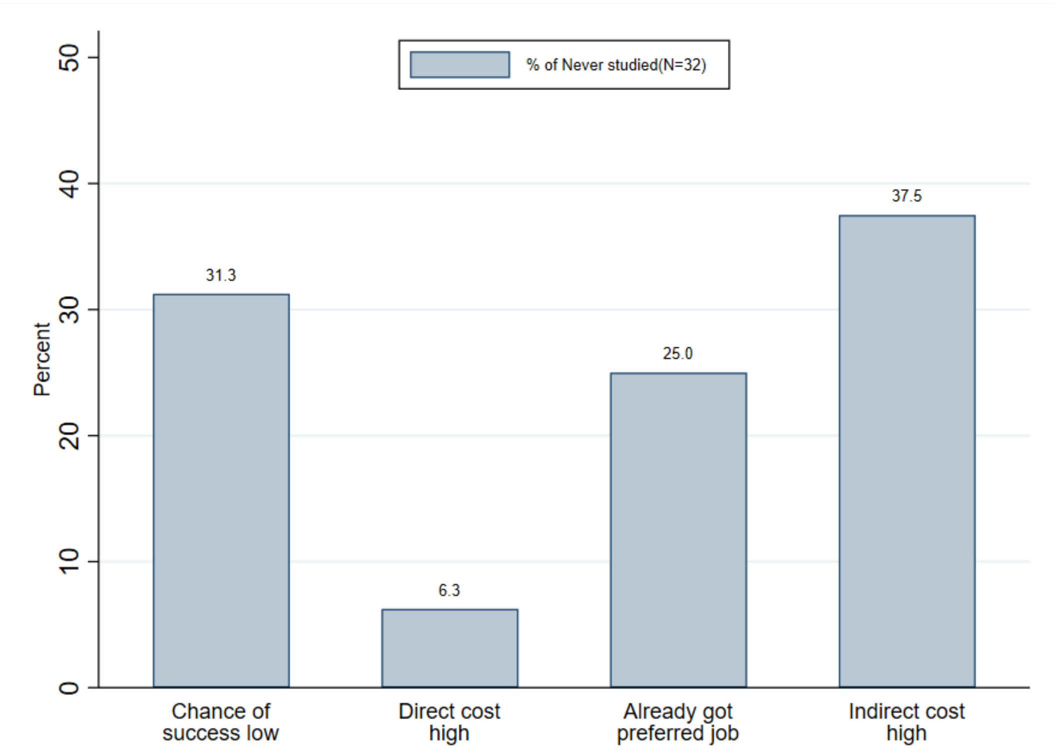
Note: Multiple option was allowed, percent is of total response, not total respondent

Figure 7: Do you think your preparation for government jobs (e.g., study material, networking, etc.) is useful per se in the labor market for other jobs or professions apart from government jobs?



Multiple response not allowed, so the number of responses and respondents is same.

Figure 8: Why have you never studied for government jobs? (please choose all that apply)



Note: Multiple option was allowed, percent is of total response, not total respondent

Appendix

Appendix 1. Supplementary: Subgroup results

Table A1.1: Effect of job entry age-ceiling policy on employment by sex and education, 1991–2017

Dependent Variable: Employment status (0/1)							
Panel A: Male. Employment status with education ≥8				Panel B: Male. Employment status with education <8			
Age>30	0.009	-0.010	0.026**	Age>30	-0.024	0.008	0.013
	(0.017)	(0.016)	(0.010)		(0.024)	(0.008)	(0.009)
Mean at age 30	0.899***	0.887***	0.865***	Mean at age 30	0.963***	0.910***	0.918***
	(0.016)	(0.015)	(0.007)		(0.023)	(0.007)	(0.007)
Observations	2,659,516	2,858,760	2,858,760	Observations	5,457,846	6,101,485	6,101,485
Panel C: Female. Employment status with education ≥8,				Panel D: Female. Employment status with education <8			
Age>30	0.031**	0.047***	0.047***	Age>30	0.056***	0.041***	0.042**
	(0.012)	(0.008)	(0.009)		(0.012)	(0.014)	(0.017)
Mean at age 30	0.218***	0.191***	0.193***	Mean at age 30	0.140***	0.146***	0.147***
	(0.010)	(0.004)	(0.005)		(0.006)	(0.007)	(0.008)
Observations	1,838,580	1,882,017	1,882,017	Observations	6,344,265	6,998,692	6,998,692
Age group	15-50	15-60	15-60	Age group	15-50	15-60	15-60
Spline	Linear	Quadratic	Cubic	Spline	Linear	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of likelihood of being employed of turning 31 years old for the age 15–60 male and female of two education group. Male population with education≥8 grade in Panel A and with education<8 grade in Panel B. Female population with education≥8 grade in Panel C and with education<8 grade in Panel D. The 1991–2017 pooled data consists of population census 1991, population census 2001, LFS 2002-03, LFS 2005-06, LFS 2010, population census 2011, LFS 2013, QLFS 2015-16, QLFS 2016-17. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A1.2: Effect of job entry age-ceiling policy on employment, all individuals 1991–2017

	Dependent Variable: Employment status (0/1)					
	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	0.044**	0.061***	0.039***	0.040***	0.027	0.011
	(0.017)	(0.016)	(0.010)	(0.009)	(0.021)	(0.027)
Mean at age 30	0.507***	0.497***	0.466***	0.469***	0.484***	0.497***
	(0.015)	(0.008)	(0.005)	(0.002)	(0.018)	(0.026)
Observations	5,431,078	5,431,078	7,044,983	7,044,983	108,192	108,192
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.032	0.048	0.067***	0.037	-0.007	0.023*
	(0.030)	(0.031)	(0.023)	(0.029)	(0.016)	(0.014)
Mean at age 30	0.481***	0.423***	0.471***	0.479***	0.502***	0.497***
	(0.029)	(0.029)	(0.007)	(0.011)	(0.009)	(0.007)
Observations	107,500	107,500	115,247	115,247	4,320,681	4,320,681
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	0.081	0.107	0.018	0.045***	0.041***	0.039**
	(0.056)	(0.067)	(0.012)	(0.015)	(0.011)	(0.016)
Mean at age 30	0.545***	0.505***	0.552***	0.549***	0.566***	0.574***
	(0.030)	(0.014)	(0.006)	(0.004)	(0.004)	(0.007)
Observations	97,342	97,342	310,841	310,841	305,090	305,090
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

Notes: OLS Regression discontinuity estimates of likelihood of turning 31 years old of being employed at age turning 31 for the age group 15–60 for all individuals. Panel A–I presents each year result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A1.3: Effect of job entry age-ceiling policy on employment, individuals with education ≥8 1991–2017
Dependent Variable: Employment status (0/1)

	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	0.019	0.032***	0.039**	0.055***	-0.007	-0.030
	(0.023)	(0.010)	(0.019)	(0.011)	(0.019)	(0.028)
Mean at age 30	0.715***	0.694***	0.576***	0.584***	0.544***	0.565***
	(0.023)	(0.009)	(0.015)	(0.009)	(0.016)	(0.026)
Observations	947,295	947,295	1,867,739	1,867,739	40,965	40,965
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.032	0.046	0.066**	0.031	0.0010	0.039***
	(0.027)	(0.030)	(0.032)	(0.038)	(0.020)	(0.012)
Mean at age 30	0.521***	0.477***	0.486***	0.500***	0.581***	0.567***
	(0.023)	(0.024)	(0.007)	(0.006)	(0.017)	(0.009)
Observations	44,466	44,466	45,728	45,728	1,476,467	1,476,467
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	0.116***	0.168***	-0.002	0.030**	0.015*	0.033***
	(0.035)	(0.031)	(0.012)	(0.013)	(0.008)	(0.009)
Mean at age 30	0.564***	0.536***	0.563***	0.556***	0.571***	0.572***
	(0.025)	(0.013)	(0.009)	(0.006)	(0.003)	(0.003)
Observations	48,022	48,022	134,788	134,788	135,307	135,307
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of turning 31 years old estimates of likelihood of being employed for the age 15–60 for individuals with education ≥8 grade. Panel A–I presents each year result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A1.4: Effect of job entry age-ceiling policy on employment with education $\geq$8 1991–2017, male
Dependent Variable: Employment status (0/1)

	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	-0.008	0.017***	0.047	0.036*	-0.010	-0.040
	(0.023)	(0.005)	(0.028)	(0.021)	(0.024)	(0.024)
Mean at age 30	0.930***	0.903***	0.817***	0.830***	0.836***	0.838***
	(0.023)	(0.005)	(0.028)	(0.020)	(0.016)	(0.020)
Observations	681,590	681,590	1,139,493	1,139,493	23,373	23,373
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.048	0.039	0.044*	0.054	-0.033	0.023***
	(0.039)	(0.027)	(0.025)	(0.036)	(0.021)	(0.008)
Mean at age 30	0.848***	0.781***	0.794***	0.796***	0.948***	0.913***
	(0.038)	(0.024)	(0.008)	(0.008)	(0.020)	(0.007)
Observations	25,390	25,390	24,701	24,701	799,457	799,457
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	-0.020	0.069***	-0.015	0.035***	-0.024**	0.004
	(0.039)	(0.021)	(0.016)	(0.009)	(0.011)	(0.011)
Mean at age 30	0.947***	0.886***	0.903***	0.882***	0.909***	0.896***
	(0.037)	(0.018)	(0.013)	(0.004)	(0.009)	(0.005)
Observations	25,655	25,655	69,904	69,904	69,197	69,197
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of likelihood of being employed of turning 31 years old for the age 15–60 for male population with education $\geq$8 grade. Panel A–I presents each year result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A1.5: Effect of job entry age-ceiling policy on employment with education ≥8 1991–2017, female

	Dependent Variable: Employment status (0/1)					
	Panel A: 1991		Panel B: 2001		Panel C: 2002-03	
Age>30	0.017	0.018**	0.018	0.040***	0.024*	0.001
	(0.012)	(0.008)	(0.015)	(0.014)	(0.013)	(0.023)
Mean at age 30	0.144***	0.137***	0.179***	0.173***	0.163***	0.190***
	(0.006)	(0.002)	(0.008)	(0.006)	(0.012)	(0.020)
Observations	265,705	265,705	728,246	728,246	17,592	17,592
	Panel D: 2005-06		Panel E: 2010		Panel F: 2011	
Age>30	-0.022	-0.016	0.060*	0.021	0.022**	0.031***
	(0.016)	(0.019)	(0.033)	(0.040)	(0.010)	(0.009)
Mean at age 30	0.150***	0.136***	0.147***	0.166***	0.137***	0.142***
	(0.008)	(0.012)	(0.011)	(0.007)	(0.003)	(0.004)
Observations	19,076	19,076	21,027	21,027	677,010	677,010
	Panel G: 2013		Panel H: 2015-16		Panel I: 2016-17	
Age>30	0.116***	0.114**	0.018	0.039**	0.055***	0.056***
	(0.040)	(0.046)	(0.015)	(0.017)	(0.015)	(0.021)
Mean at age 30	0.159***	0.166***	0.247***	0.242***	0.278***	0.280***
	(0.023)	(0.016)	(0.012)	(0.012)	(0.006)	(0.007)
Observations	22,367	22,367	64,884	64,884	66,110	66,110
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

Notes: OLS regression discontinuity estimates of turning 31 years old on female employment with education ≥8 1991–2017 for the age 15–60 for female population with education ≥8 grade. Panel A–I presents each year result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

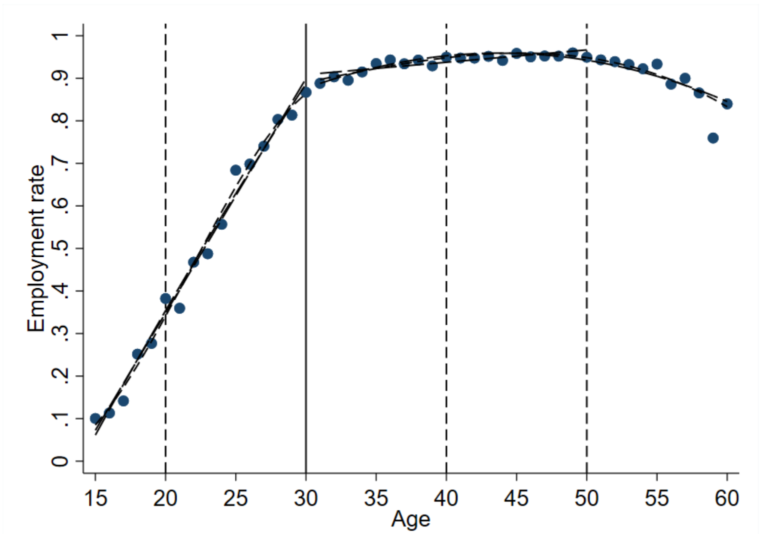
Table A1.6: Job entry age-ceiling for effect on labor force over not labor force, and on employment over unemployment

	Labor force vs. not labor force					
	All		Male		Female	
Age>30	0.036**	0.054***	-0.013	0.022**	0.052***	0.052***
	(0.013)	(0.013)	(0.0128)	(0.00882)	(0.013)	(0.015)
Mean at age 30	0.531***	0.523***	0.932***	0.913***	0.177***	0.180***
	(0.010)	(0.006)	(0.012)	(0.008)	(0.006)	(0.008)
Observations	17,840,954	17,840,954	8,960,245	8,960,245	8,880,709	8,880,709
	Employment vs. unemployment					
Age>30	-0.000	-0.000	0.003	0.001	-0.004	0.004
	(0.003)	(0.002)	(0.003)	(0.002)	(0.010)	(0.010)
Mean at age 30	0.963***	0.961***	0.978***	0.977***	0.893***	0.890***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)
Observations	8,270,243	8,270,243	7,388,405	7,388,405	881,838	881,838
Spline	Quadratic	Cubic	Quadratic	Cubic	Quadratic	Cubic

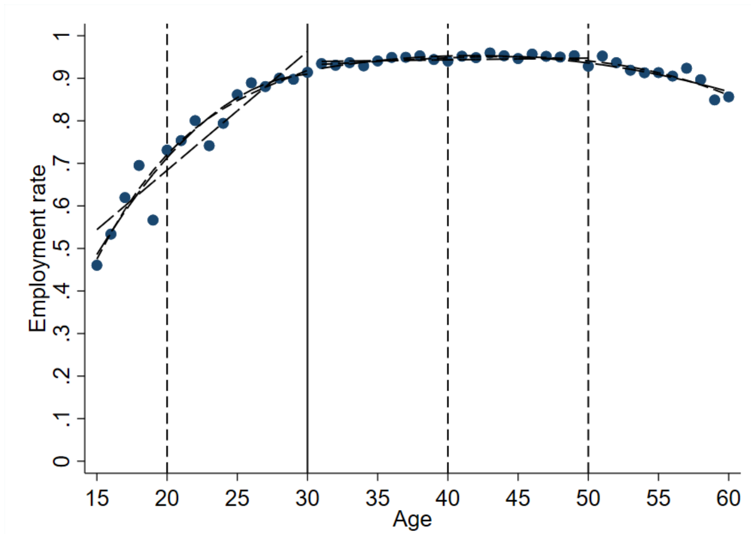
Notes: OLS regression discontinuity estimates of turning 31 years old for labor force over not labor force, and for employment over unemployment for the period 1991–2017 and age group 15–60.
Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Figure A1.1: Effect of job entry age-ceiling policy on employment by sex and education, 1991–2017

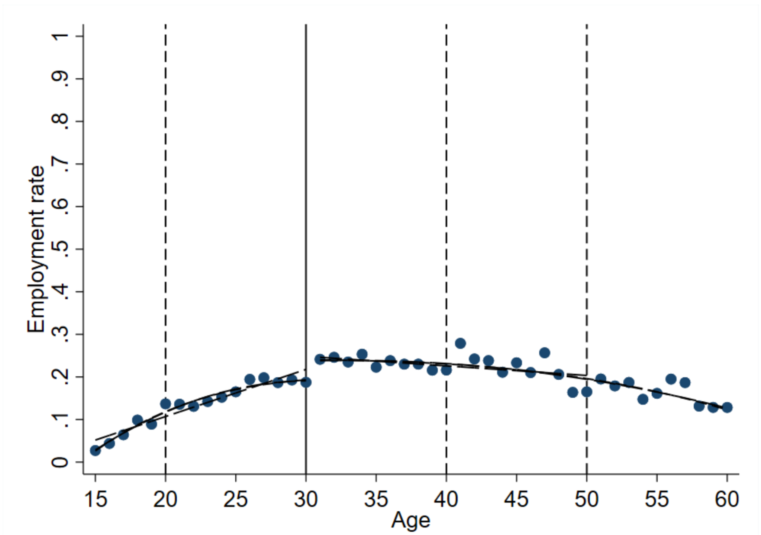
Panel A: Employment status of males with education ≥ 8



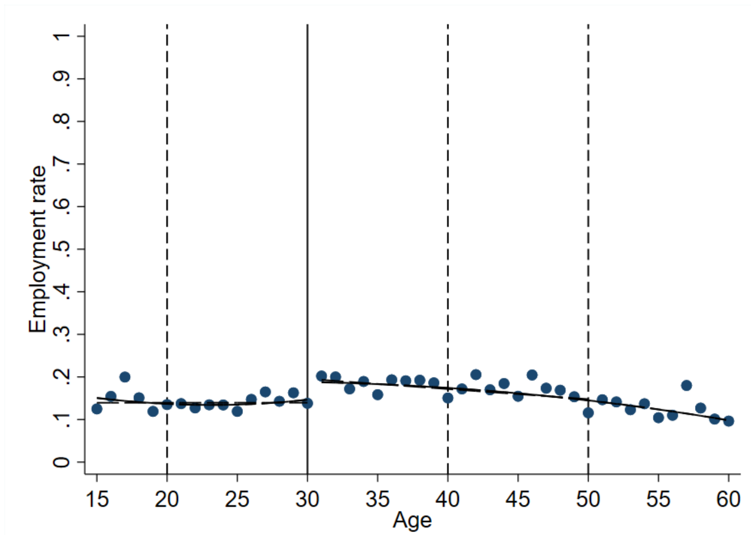
Panel B: Employment status of males with education <8



Panel C: Employment status of females with education ≥ 8



Panel D: Employment status of females with education <8



Notes: Panel A ,Panel B Panel C, Panel D correspond the result respective Panels in Table A1.1.

Appendix 2. Falsification, robustness and validation check

Table A2.1: Effect of job entry age-ceiling policy on education, 1991–2017

	Dependent variable: Education grade (0/1)		
	Panel A: Education dummy for at least 8 grade		
Age>30	-0.001	0.023	0.047*
	(0.021)	(0.021)	(0.024)
Mean at age 30	0.349***	0.334***	0.346***
	(0.016)	(0.013)	(0.019)
Observations	16,300,207	17,840,954	17,840,954
	Panel B: Education dummy for above 5 grade		
Age>30	0.000	0.017	0.058***
	(0.022)	(0.024)	(0.021)
Mean at age 30	0.400***	0.397***	0.395***
	(0.017)	(0.017)	(0.018)
Observations	16,300,207	17,840,954	17,840,954
Age group	15-50	15-60	15-60
Spline	Linear	Quadratic	Cubic

Notes: As a robustness check, OLS regression discontinuity estimates of likelihood of having specified education grade at turning 31 years old for the age group between 15 and 60. Panel A and Panel B respectively presents likelihood of 8 grade of education and 5 grade of education for all individuals. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A2.2: Effect of job entry age-ceiling policy on work hour of employed male, 2003–2017

Dependent Variable: Weekly male work hour

Panel A: 2002-03			Panel B: 2005-06			Panel C: 2010		
Age>30	0.0522	-0.408	Age>30	-0.438	0.00139	Age>30	-0.547	-0.766
	(0.466)	(0.393)		(0.502)	(0.688)		(0.406)	(0.644)
Mean at age 30	46.91***	47.12***	Mean at age 30	54.25***	54.21***	Mean at age 30	53.64***	53.66***
	(0.429)	(0.320)		(0.239)	(0.260)		(0.132)	(0.126)
Observations	41,170	41,170	Observations	41,276	41,276	Observations	42,876	42,876

Panel D: 2013			Panel D: 2015-16			Panel F: 2016-17		
Age>30	0.207	-1.152	Age>30	0.077	0.064	Age>30	-0.562**	-0.217
	(0.700)	(1.038)		(0.209)	(0.216)		(0.230)	(0.329)
Mean at age 30	48.99***	49.74***	Mean at age 30	56.04***	55.85***	Mean at age 30	55.75***	55.67***
	(0.564)	(0.902)		(0.154)	(0.0721)		(0.0921)	(0.0849)
Observations	36,791	36,791	Observations	117,442	117,442	Observations	113,571	113,571
Age group	15-60	15-60		15-60	15-60		15-60	15-60
Spline	Quadratic	Cubic		Quadratic	Cubic		Quadratic	Cubic

Notes: As a robustness check at intensive margin, OLS regression discontinuity estimates of turning 31 years old on work hour for the age 15–60 of employed male individuals. Panel A–F presents survey year's result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and *for the 10% level.

Table A2.3: Effect of job entry age-ceiling policy on work hour of employed female, 2003–2017

Dependent Variable: Weekly female work hour								
Panel A: 2002-03			Panel B: 2005-06			Panle C: 2010		
Age>30	0.112	1.218	Age>30	-0.286	-4.112***	Age>30	-3.537***	-4.702**
	(0.705)	(0.726)		(1.401)	(1.465)		(0.842)	(1.792)
Mean at age 30	34.03***	33.57***	Mean at age 30	42.77***	44.22***	Mean at age 30	52.22***	52.08***
	(0.514)	(0.237)		(0.755)	(0.559)		(0.323)	(0.330)
Observations	7,269	7,269	Observations	6,437	6,437	Observations	8,720	8,720
Panel D: 2013			Panel E: 2015-16			Panel F: 2016-17		
Age>30	-0.345	-0.552	Age>30	-0.790	-0.739	Age>30	-0.547	-1.439
	(0.843)	(1.041)		(0.584)	(0.577)		(1.026)	(1.149)
Mean at age 30	46.41***	46.75***	Mean at age 30	46.88***	46.13***	Mean at age 30	42.05***	42.17***
	(0.776)	(0.905)		(0.286)	(0.353)		(0.801)	(0.883)
Observations	8,655	8,655	Observations	34,086	34,086	Observations	38,161	38,161
Spline	Quadratic	Cubic	Spline	Quadratic	Cubic	Spline	Quadratic	Cubic

Notes: As a robustness check at intensive margin, OLS regression discontinuity estimates of turning 31 years old on work hour for the age 15–60 of employed female individuals. Panel A–F presents survey year's result. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A2.4: Effect of job entry age-ceiling policy on employment (excl. age 30), 1991–2017

	Dependent variable: Employment status (0/1)		
	Panel A: All		
age>30	0.0323***	0.0145	0.0255
	(0.00922)	(0.0134)	(0.0210)
Mean at age 30	0.532***	0.532***	0.528***
	(0.00551)	(0.0106)	(0.0176)
Observations	15,038,843	16,579,590	16,579,590
	Panel B: Male		
age>30	-0.0383*	-0.0265	0.0342
	(0.0200)	(0.0242)	(0.0352)
Mean at age 30	0.966***	0.929***	0.880***
	(0.0192)	(0.0240)	(0.0351)
Observations	7,515,024	8,357,907	8,357,907
	Panel C: Female		
age>30	0.0320**	0.0369**	0.0132
	(0.0119)	(0.0138)	(0.0168)
Mean at age 30	0.180***	0.168***	0.193***
	(0.00699)	(0.00891)	(0.0113)
Observations	7,523,819	8,221,683	8,221,683
Age group	15-50	15-60	15-60
Spline	Linear	Quadratic	Cubic

Notes: As a robustness check, OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the age between 15 and 60 for all individuals excluding who reported their age 30. Panel A presents male and female together, Panel B Male and Panel C Female. The pooled datasets are LFS Census 1991, census 2001, 2002-03, LFS 2005-06, LFS 2010, LFS 2013, QLFS 2015-16, QLFS 2016-17. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Table A2.5: Effect of job entry age-ceiling policy on employment (excl. public service) 2003–2017

Dependent Variable: Employment status (0/1)			
Panel A: Total employment rate by age			
Age>30	0.052***	0.046***	0.066***
	(0.015)	(0.017)	(0.016)
Mean at age 30	0.477***	0.464***	0.452***
	(0.012)	(0.012)	(0.007)
Observations	816,220	920,427	920,427
Panel B: Male employment rate by age			
Age>30	-0.001	-0.012	0.038***
	(0.021)	(0.021)	(0.011)
Mean at age 30	0.922***	0.903***	0.874***
	(0.020)	(0.020)	(0.010)
Observations	371,690	423,352	423,352
Panel C: Female employment by age			
Age>30	0.043***	0.046***	0.039**
	(0.010)	(0.010)	(0.015)
Mean at age 30	0.174***	0.162***	0.163***
	(0.007)	(0.004)	(0.005)
Observations	444,530	497,075	497,075
Age group	15-50	15-60	15-60
Model	Linear	Quadratic	Cubic

Notes: As a robustness check, OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the age between 15 and 60 for all individuals excluding who has already secured a government job. Panel A presents male and female together, Panel B Male and Panel C Female. The pooled datasets are LFS 2002-03, LFS 2005-06, LFS 2010, LFS 2013, QLFS 2015-16, QLFS 2016-17. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

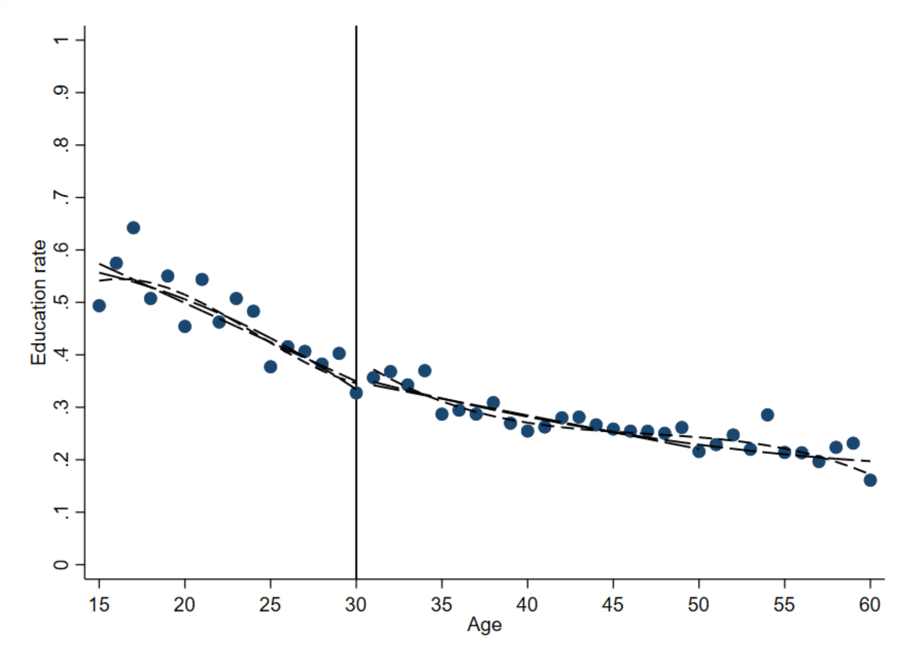
Table A2.6: Effect of job entry age-ceiling policy on employment, 2003–2017

	Dependent variable: Employment status (0/1)			
	Panel A: All			
Age>30	0.0371**	0.0376**	0.0373**	0.0387**
	(0.0162)	(0.0162)	(0.0163)	(0.0156)
Mean at age 30	0.527***	0.551***	0.559***	0.581***
	(0.0102)	(0.0100)	(0.0100)	(0.0111)
Observations	936,020	936,020	936,020	936,020
	Panel B: Male			
Age>30	-0.0103	-0.0103	-0.0101	-0.0103
	(0.0169)	(0.0169)	(0.0168)	(0.0168)
Mean at age 30	0.913***	0.911***	0.916***	0.910***
	(0.0162)	(0.0161)	(0.0162)	(0.0166)
Observations	458,895	458,895	458,895	458,895
	Panel C: Female			
Age>30	0.0448***	0.0448***	0.0442***	0.0479***
	(0.0129)	(0.0128)	(0.0129)	(0.0115)
Mean at age 30	0.202***	0.245***	0.252***	0.311***
	(0.00496)	(0.00708)	(0.00907)	(0.00936)
Observations	477,125	477,125	477,125	477,125
Age group	15-60	15-60	15-60	15-60
Model	Quadratic	Quadratic	Quadratic	Quadratic
Rural-urban		yes	yes	yes
Division			yes	yes
Year				yes

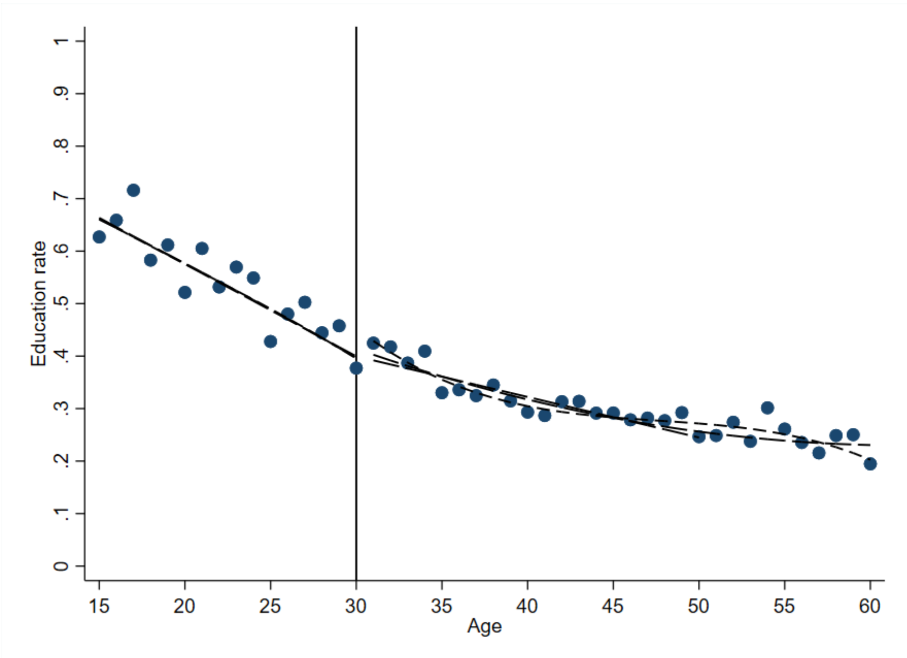
Notes: As a robustness check, OLS regression discontinuity estimates of likelihood of being employed at turning 31 years old for the age between 15 and 60 with controlling for geographic variables—rural-urban, division and year dummy. Panel A presents male and female together, Panel B Male and Panel C Female. The pooled datasets are LFS 2002-03, LFS 2005-06, LFS 2010, LFS 2013, QLFS 2015-16, QLFS 2016-17. Standard errors clustered at age level in parentheses. *** Indicates statistical significance at the 1% level, ** for the 5% level, and * for the 10% level.

Figure A2.1: Age effect on education, 1991–2017 pooled

Panel A: Dummy for eduction at least 8 grade



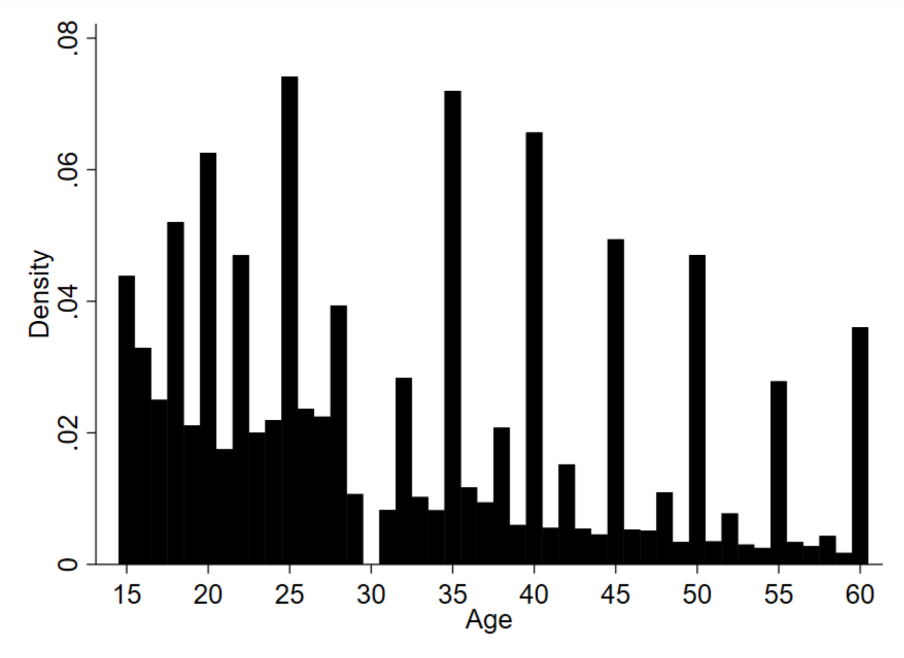
Panel B: Dummy for education above 5 grade



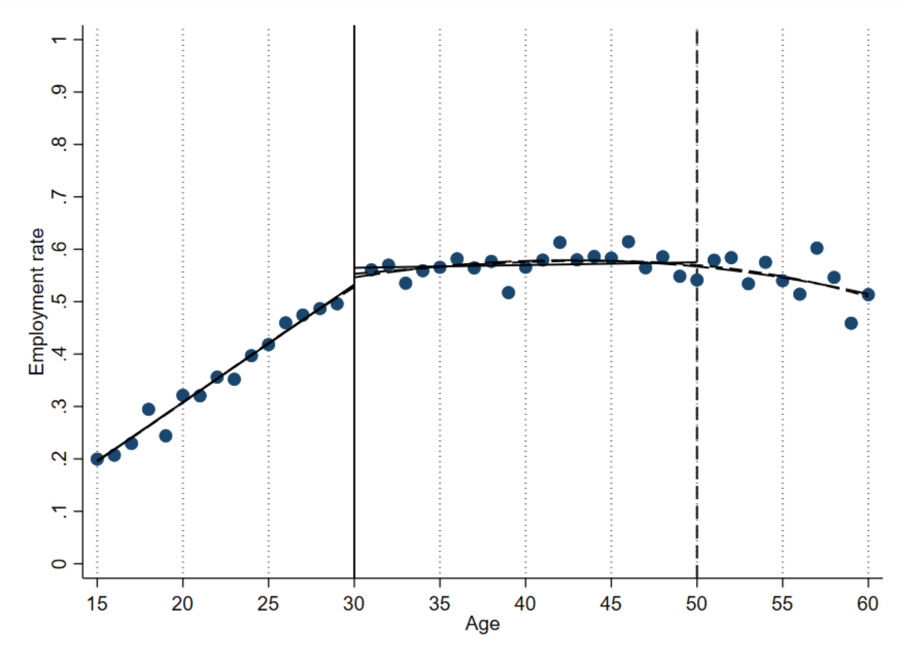
Notes: Figure A2.1 corresponds the result of Table A2.1.

Figure A2.4.1: Age histogram and estimates of turning 31 years old on employment for all age and sex group together, 1991–2017 pooled (excl. age 30)

Panel A: Histogram of discrete age variable



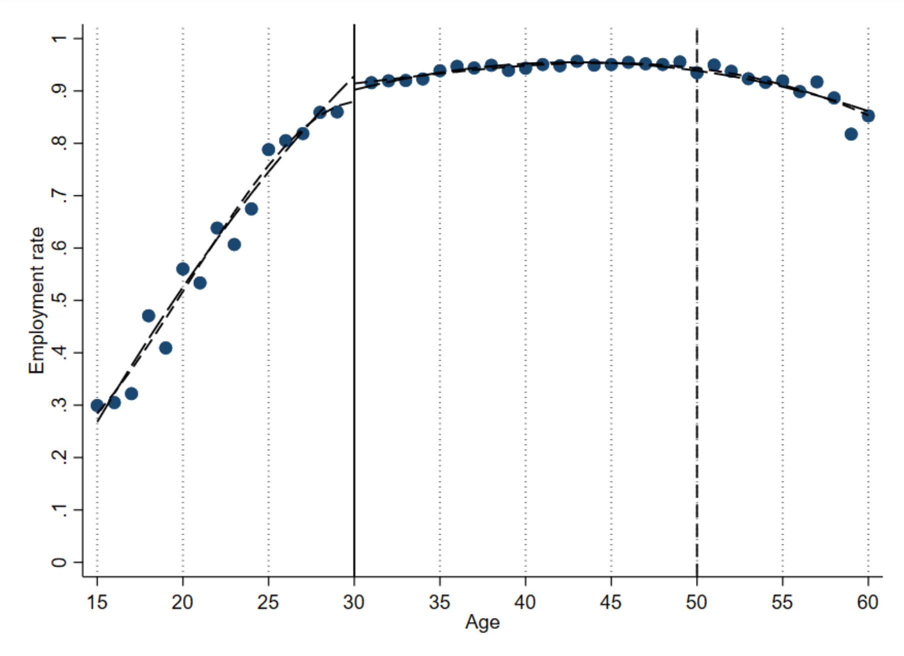
Panel B: Effect of turning 31 years old on employment(excl. age 30)



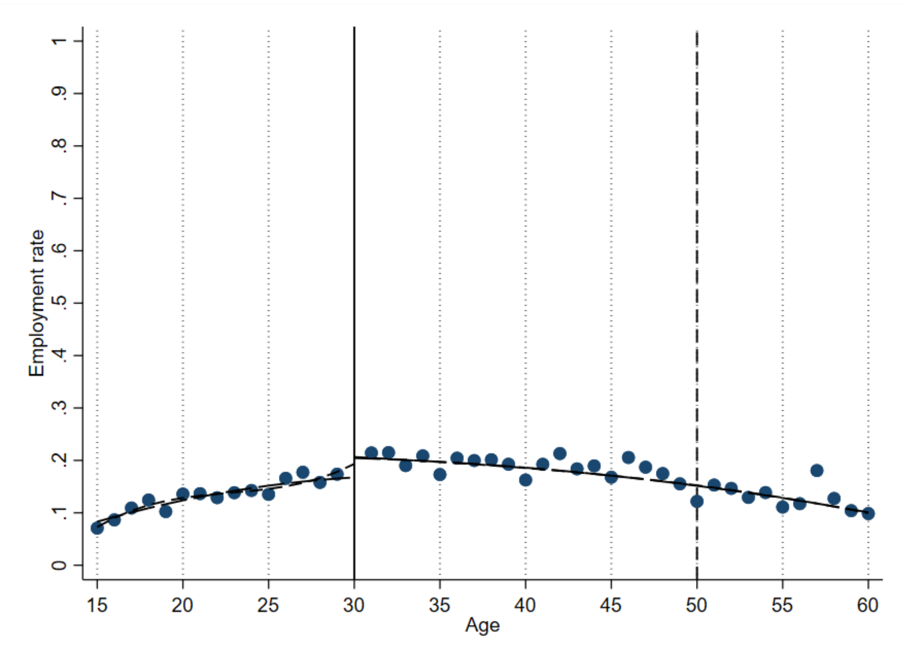
Notes: Panel B corresponds the Panel A of Table A2.4

Figure A2.4.2: Employment rate by sex (excl. age 30), 1991–2017

Panel A: Male



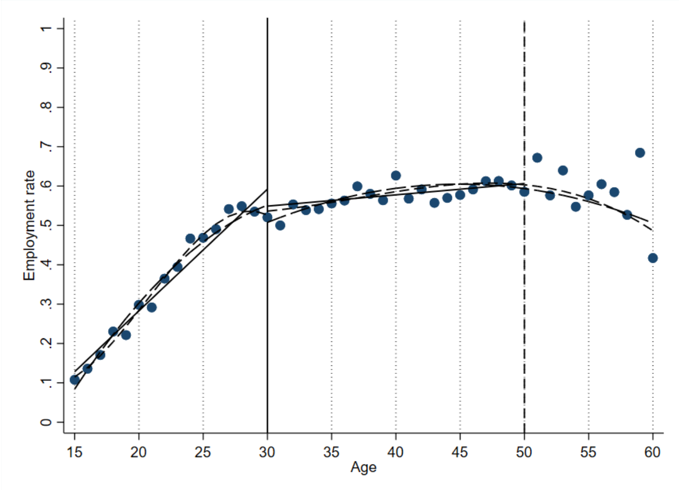
Panel B: Female



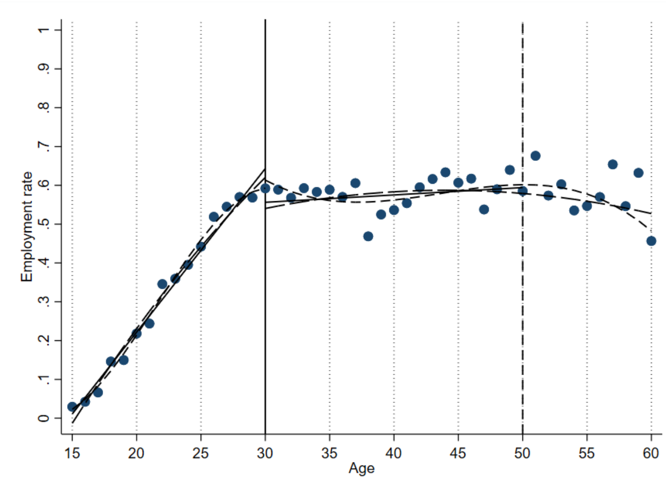
Notes: Panel A and Panel B correspond respectively to the regression Panel B and Panel C of Table A2.4

Figure A2.5: Employment rate by age, West Bengal

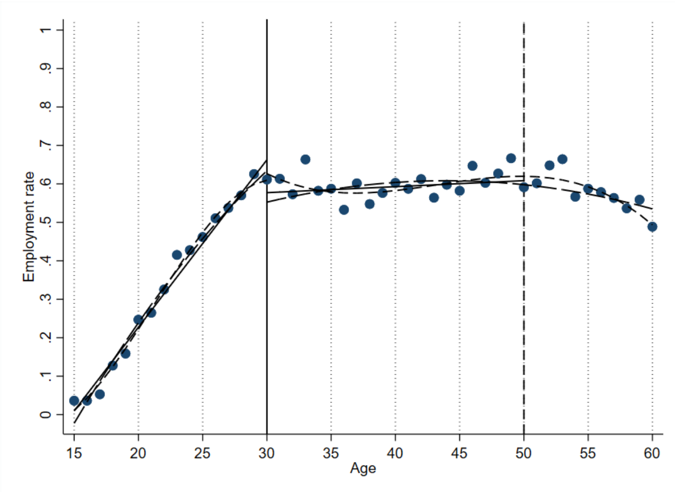
Panel A: 2011-12



Panel B: 2017-18



Panel C: 2019-20



Notes: As a falsification exercise, extrapolated at age 30 figure from OLS regression discontinuity estimates for the individuals of Indian state of West Bengal; the state borders Bangladesh, speaks same language, Bangla and performs similarly in economic indicators.

Employment defined based on the principal usual activity for one year. No weight is adjusted in the estimation.

Data: Employment and unemployment 2011-12; Periodic Labor Force Survey 2017-18 and 2019-2020. Collected from National Data Archive, Ministry of Statistics and Programme Implementation, India.

Appendix 3. Relevance of studying government jobs effects

Figure A3.1: Snapshot of protest to revise policy regarding government jobs

Panel A: Protest for revising quota system in the public service jobs

Source: Wikipedia, (accessed on 24 Jan 2021) https://en.wikipedia.org/wiki/2018_Bangladesh_quota_reform_movement

Panel B: Protest for raising age ceiling for public service jobs

Job seekers stage a demonstration at Shahbagh of Dhaka and later bring out a token coffin march on April 27, 2018, demanding the ceiling to be raised to 35 in government service from what it is 30 now. Photo: Prabir Das

Source: The Daily Star, (accessed on 24 Jan 2021) https://www.thedailystar.net/city/demonstration-demo-shahbagh-raising-age-ceiling-government-job-age-limit-35-bangladesh-1568647

Table A3.1: A brief summary of public services examinations

Exam authority	Type	Exam pattern briefly
PSC	BCS	Under 'BCS Recruitment Rule 2014', PSC arranges 3-steps exam for 26 cadre to select candidate. Till 34th BCS, Preliminary test were 100 marked, under 2014 rule 200 marked exam for 2 hours on 10 topics initiated from 35th BCS. Steps with marks distribution are below. *Step 1.* 200 marks MCQ Type Preliminary Test: (Bengali language & literature 35; English language & literature 35; Bangladesh affairs 30; International affairs 20; Geography (Bangladesh & global), environment & disaster management 10; General science 15; Computer & information technology 15; Mathematical logic 15; Mental aptitude 15; Moral, values & good-governance 10). *Step 2.* 900 marks written test (average pass mark 50%): Those who pass preliminary exam take one or both of this two category exam- general cadre and technical/professional cadre. (General: Bengali 200; English 200; Bangladesh affairs 200; International affairs 100; Mathematical logic & mental aptitude 100; General science and technology 100. Technical/Professional: Bengali 100; English 200; Bangladesh affairs 200; International affairs 100; Mathematical logic & mental aptitude 100; Post related topic 200.) *Step 3.* 200 marks viva voce (pass mark 50%): Those who pass written exam take part in oral exam.
	Non-cadre	Revised on 27 February 2019. This exam is to fill up the vacancy through PSC for non-cadre technical/professional & non-technical positions (9th & 10th to 13th grade) of different ministries/divisions. 9th grade technical/professional: If number of applicant is 1000 or less, 200 marks written exam for 4 hours (Bengali 40; English 40; General knowledge 40; relevant technical/professional subject 80. Pass marks: aggregate 45% and technical/professional 30%). If number of applicant is more than 1000, first 100 marks MCQ for one hour (Bengali 20; English 20; General knowledge (Bangladesh & international affairs) 20; relevant technical/professional subject 40). The selected candidate in MCQ take part in the above test of 200 marks. The selected candidate in written exam attend 100 marks viva voce exam, pass marks 45%. 10-13th grade technical/professional: Similar arrangement and marks distribution as 9th grade; in this case viva voce is for 50 marks and pass 40%. 9th grade non-technical: If number of applicant is 1000 or less, 200 marks written exam for 4 hours (Bengali 50; English 50; General knowledge 40; Math and mental aptitude 60. Pass marks: aggregate 45%). If number of applicant is more than 1000, first 100 marks MCQ for one hour (Bengali 25; English 25; General knowledge (Bangladesh & international affairs) 25; Math and general science 25). The selected candidate in MCQ take part in the above test of 200 marks. The selected candidate in written exam attend 100 marks viva voce exam, pass marks 45%. 10-13th grade technical/professional: Similar arrangement and marks distribution as 9th grade; in this case viva voce is for 50 marks and pass 40%.
	Departmental Examination	There are 26 different cadres of the Bangladesh civil service. Every officer of the entry level posts of a cadre service must qualify in a departmental examination conducted by the Public Service Commission. The BPSC also conducts departmental examinations for certain categories of non cadre services. The examination is held twice a year, preferably in June and December.

Note: Based on http://www.bpsc.gov.bd/ (accessed 14 December 2021)

Table A3.2: Countries that have some age ceiling policy

Country	Age ceiling	Other information
Bangladesh	30	in general
Pakistan	30 & 32	may have categories
Sri Lanka	45	
Nepal	between 35 & 42	a few categories
India	between 32 & 44	various categories
Nigeria	30	abolished recently after university strike

Appendix 4. Data details

4.1 Empirical data

Table A4.1: Variables in the censuses and surveys

Census/ Survey	Interview period	Employment question	Employment answer	Emp. share
Census 1991	12 a.m. to 5 a.m., March 12, 1991	Main field of activities (last one month)	1. employed: agriculture; industry; water/electricity/gas; construction; transport/communication; business; service; other.	46.62
			2. unemployed: looking for work.	1.39
			3. HH work: hh work.	43.37
			4. not working: not working.	8.62
			8. dot (unknown).	
			9. not in the universe	
Census 2001	12 a.m. to 5 a.m., January 23, 2001	Main field of activities (last one month)	1. employed: agriculture; industry; water/electricity/gas; construction; transport/communication; hotel/restaurant; business; service; other.	42.71
			2. unemployed: looking for work.	2.29
			3. HH work: hh work.	37.57
			4. not working: not working.	17.42
			9. not in the universe	
LFS 2002-03	..	What was the status in employment of (name) where you worked last week?	1. employed: regular paid employee; employer; self-employed; day laborer; domestic worker; paid/unpaid apprentice.	44.77
			2. unemployed: If you did not have work or job attachment during last 7 days, were you available or looking for work/job? Yes.	2.72
			3. HH work: unpaid family work	10.39
			4. Not working: if zero (none of the above) and other	42.12
LFS 2005–06	October 2005–September 2006	What was your status in employment where you worked most of the time during last week?	1. employed: regular paid employee; employer; self-employed; irregular paid worker; day laborer (agri and non-agri); domestic worker; paid/unpaid apprentice.	44.38
			2. unemployed: If you did not work during last 7 days, were you prepared for job or searching job? Yes.	2.32
			3. HH work: unpaid family worker	12.61
			4. Not working: if zero (none of the above) and other.	40.69
LFS 2010	10 May 2010 - 25 May 2010	What is your employment status? (last 7 days).	1. employed: employee; employer; self-employed (agri and non-agri); casual/irregular paid worker; day laborer(agri and non-agri); domestic worker	44.77
			2. unemployed: Did you look for a paid job or try to start your own business (including the 7 days of the survey) during last 4 weeks? Yes I looked for paid job and Yes I tried to start my own business	1.75
			3. HH work: unpaid worker/ family member	13.62
			4. Not working: if dot (none of the above).	39.87

Census 2011	12 a.m. to 6 a.m., March 15, 2011	Activity status (last 7 days)	1. employed: employed. 2. unemployed: looking for work. 3. HH work: hh work. 4. not working: not working. 8. unknown (1 obs.) 9. not in the universe	44.33 1.21 39.92 14.55
LFS 2013	January 2013 - December in 2013	What is the status of her/his involvement in this job/business?	1. employed: employer; self-employed (agri and non-agri); paid employee; day laborer(agri and non-agri); apprentice/intern/trainees(paid); domestic worker. 2. unemployed: Did he/she look for job/ work during the last 1 month? Yes. 3. HH work: contributing family member. 4. Not working: if dot (none of the above) and others (specify).	46.69 3.72 9.38 40.22
LFS 2015-16	July 2015 - June 2016	What is your employment status in this work? (last week)	1. employed: employer; self-employed; paid employee; day laborer; apprentice/intern/trainees(paid); domestic worker. 2. unemployed: Did you look for job/ work during the last 1 month for pay/wage/profit? Yes. 3. HH work: contributing family member. 4. Not working: if dot (none of the above) and others (specify).	48.75 2.53 7.31 41.41
LFS 2016-17	July 2016 - June 2017	What is your employment status in this work? (last week)	1. employed: employer; self-employed; paid employee; day laborer; apprentice/intern/trainees(paid); domestic worker. 2. unemployed: Did you look for job/ work during the last 1 month for pay/wage/profit? Yes. 3. HH work: contributing family member. 4. Not working: if dot (none of the above) and others (specify).	49.73 3.17 5.81 41.30

Notes: In constructing the dummy variable for employment status we used the 'Employment answer' category 1 (employed) as 1 and all other categories as 0.

Table A4.2: Age questions in the censuses and surveys

Census/ Survey	Age question
Census 1991	Age (In completed years) (Bangla)
Census 2001	Age (In completed years) (English)
LFS 2002-03	Age (In completed years) (English)
LFS 2005–06	Age (Incompleted years, if less than one year write 00) (English)
LFS 2010	Age as of last birthday (If less than 12 months enter "00") (English)
Census 2011	Age (Completed years) (English)
LFS 2013	Age of the member (completed years) (If age<1 year >>'00' ; age≥100 >>'99') (English)
LFS 2015-16	Age (completed year) write 00 if age<1 ; write 99 if age≥99 (Bangla)
LFS 2016-17	Age (completed year) write 00 if age<1 ; write 99 if age≥99 (Bangla)

Sources: Questionnaire of censuses and surveys.

4.2 Survey data: collected through Facebook messenger

Pre-testing. In first half of February 2022, to pretest the viability of questionnaire, we sent questionnaire to 11 individuals who are familiar to us. The respondents of the pre-test comprise of public employees, private service holders, currently studying for the government jobs, and students. All 11 individuals responded.

Piloting. Based on the pretest response and discussion with respondents, we revised the questionnaire and sent to 20 members of each target group in the second half of February 2022. Piloting hints the potential response rate in final survey setting. Out of total 100 sent questionnaires, we received back only 8 responses—response rate of 8 percent. We realized that the response rate is too low probably because we sent message with questionnaire to the Facebook group member who may not be much active on Facebook or messenger. From piloting experience, we decide to send final survey questionnaire to the people who are recently active in the groups through post, like, share, and comments so that response rate improves.

Main survey. The questionnaire was finalized upon extensive discussion between researchers, pre-testing and piloting survey, and discussion with respondents of the pre-test and pilot stages. We sent questionnaires to about 1500 individuals on Facebook messenger, target individuals were chosen from five facebook groups who were recently active in the groups (Table A4.4). Within two weeks, we sent them a reminder message. The survey questionnaire was sent and open from last week of February to mid-June 2022. Since the researcher who sent the message is not connected with the sampled people on Facebook, many of them have not seen my message probably because of their messenger setting for unknown people. So the coarse response rate, calculated over total questionnaire sent, is only 16 percent. But the effective response rate, calculated over number of seen message, is 64 percent. We received 241 response against total sent questionnaire 1500.

Table A4.3. Social media profile may not be completely identifiable over time for reasons like name changes, profile delete, etc. Although we sent questionnaires to total 1500 individuals, after the survey period when count the individuals we could retrieve profile 1465 as of 13 June 2022. From available information and best guess of name of the individual, out of total 1500 individuals, we could identify the sex of 1491 individuals—1200 male, 291 female, and the remaining 9 unidentifiable from the name. Out of counted individuals of 1465, 1178 male, 283 female, and sex of 4 individuals are not identifiable. Out of 1465 individuals, only 375 individuals have seen the message and the remaining 1090 have not seen the message or questionnaire. The questionnaire actually reached to only about 26 percent of sample respondent, so total effective response rate is 64 percent based on them who have seen the message containing questionnaire and course response rate is 16 percent over number of questionnaire sent. Number of female response is very low although the response rate for male and female are close. This is simply the reflection of female participation rate in education, labor force, social media etc.

Table A4.3: Sample size and response by sex and visibility of questionnaire

Sex	Frequency					Response rate(%)	
	Sent	Count	Unseen	Seen	Response	Coarse	Effective
M	1200	1178	857	321	181	15	56
F	291	283	230	53	28	10	53
Total	1500	1465	1090	375	241*	16	64

Note: There is little mismatch between sex disagregation and total because all the individuals are not identifiable by male and female sex. There are cases of unidentified sex within seen and unseen, missing seen/unseen within sex, and unwilling to report sex.
(* 214 after dropping those who did not answer a single question)

Table A4.4 presents features of target groups on the Facebook from which we draw the sample. We present the groups' name and information anonymously.

Table A4.4: Characteristics of sample Facebook groups

Features	Group 1	Group 2	Group 3	Group 4	Group 5
Related to	Govt job preparation	Govt job preparation	Govt employee	Public university student	Private university student
Group	Public	Public	Private	Public	Private
Member	101,694	44,501	35,000	13,167	38,257
About	Platform for all government jobs to share knowledge and help each other	No details, mention of some public exams like BCS, banks	All employee of grade 1-20 to discuss various issues related to job	Career club to make students competent for the professional world, in home and abroad	Created for the students of private universities to be united and discuss about problems and help each other
Piloting	20	21	-	20	20
Survey	500	500	500	500	500
Response	49	48	33	50	61
Chat message with survey link: We request you to respond to a 5-10 minutes survey related to preparation for government jobs. Thank you. (In Bangla)					

Initially, I received total response 241 out of total questionnaire sent 1500. 27 individuals did not respond to any questions except 'I agree', so we drop them at the beginning. We dropped six observations for inconsistent response. Therefore total observation is 208 for analysis. However, response number for each question is different because respondent had the option to decide whether to answer or not for every question.

Descriptive statistics of online survey in the following tables and figure

Table A4.5: Characteristics of the respondents (%)

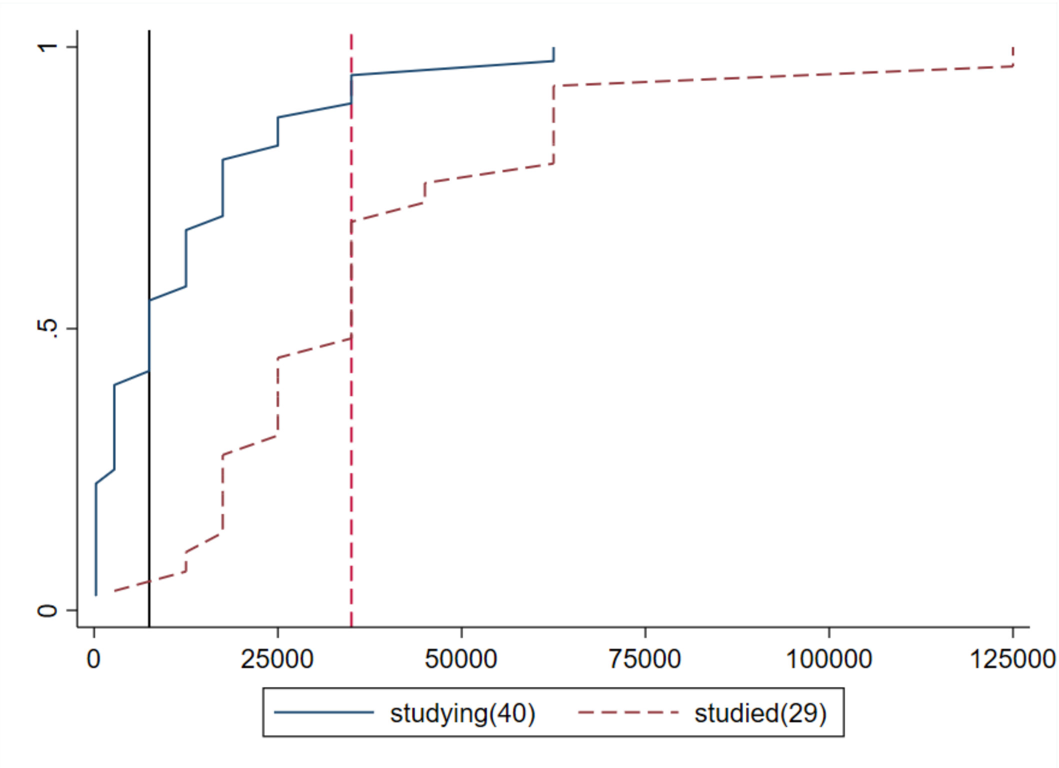
Characteristics	Study status				Total
	Studying	Studied	Will	Never	
Sex (N)	85	38	48	34	205
Female	16.47	2.63	20.83	8.82	13.66
Male	83.53	94.74	79.17	88.24	85.37
Prefer not to disclose	0.00	2.63	0.00	2.94	0.98
Age (N)	85	38	49	34	206
16-20 years	5.88	2.63	34.69	14.71	13.59
21-25 years	25.88	5.26	48.98	41.18	30.10
26-30 years	61.18	18.42	14.29	35.29	37.86
31-35 years	7.06	34.21	0.00	5.88	10.19
36-40 years	0.00	28.95	0.00	2.94	5.83
Above 40 years	0.00	10.53	2.04	0.00	2.43
Education (N)	80	38	48	33	199
Below HSC(<12 grade)	3.75	0.00	10.42	3.03	4.52
HSC/equiv.(12 grade)	5.00	2.63	41.67	15.15	15.08
Undergrad	8.75	2.63	29.17	36.36	17.09
Bachelor	33.75	13.16	12.50	24.24	23.12
Master	45.00	78.95	6.25	21.21	38.19
Other (dip,tech)	3.75	2.63	0.00	0.00	2.01
Current situation (N)	62	32	35	32	161
Fulltime gov job	25.81	62.50	0.00	0.00	22.36
Fulltime non-gov job	9.68	21.88	2.86	21.88	13.04
Own business(f/p/f/i)	6.45	0.00	8.57	15.63	7.45
Fulltime study	20.97	3.13	48.57	28.13	24.84
Study & parttime work	16.13	0.00	25.71	21.88	16.15
Looking for any work	20.97	12.50	11.43	6.25	14.29
Other	0.00	0.00	2.86	6.25	1.86

Table A4.6: Job preference by study status (job attended or wish to attend)

Job type	Frequency				
	Studying attended	Studying to attend	Studied attended	Will to attend	Total
Any government job	31	8	21	15	75
Any BCS job	14	8	17	14	53
Public bank job	16	4	12	10	38
Autonomous public ins (eg, central bank, research organization)	12	3	9	12	36
NSI job	15	2	5	7	29
School (primary, secondary) teaching job	9	4	6	4	23
Auditor job	12	2	5	3	22
Computer operator job	7	-	7	1	15
Office assistant job	10	-	4	-	14
Other	4	3	1	6	14
Total	130	34	87	72	319

Survey question: What kind of government job exams have you attended? or plan/wish to attend? (Please choose all options that apply).
Categories are: Studying attended- currently studying and attended before, Studying to attend- currently studying and will attend for the first time, Studied attended- Studied and attended before, Will to attend- Will attend in the future.

Figure A4.1: Cumulative distribution of monthly income(Taka)



Note: The vertical lines are the median values.