What Matters Most for Long Term Labor Market Outcomes: Human Capital or Signalling?*

Somdeep Chatterjee[†] ⓡ Jai Kamal[‡]

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Abstract

A strand of literature on *returns to education* suggests potential labor market consequences of a high-school diploma. However, it is difficult to empirically test apart the two underlying channels through which such returns may be generated; ie, accumulation of human capital or the value of the signal that the diploma carries. In this paper, we exploit a unique policy experiment from the Indian state of Uttar Pradesh which enacted a law to enforce stricter vigilance in prevention of unfair means in public examinations by making copying and question-leaks cognizable non-bailable offences. Following this reform, a massive decline in percentages of students graduating high school was recorded in the state suggesting prevalence of malpractices in the absence of such a law. We take advantage of plausibly exogenous cohort-variation in individuals potentially exposed to this reform in the state and employ a difference-in-differences identification strategy to find that in response to the policy, average long term hourly wages increase for individuals who graduated despite the enhanced vigilance and also the ones who could not graduate, suggesting that signalling does not necessarily play a major role in long term labor market outcomes. We further find that the ones who graduated despite vigilance have a much higher wage, potentially supporting the human capital and productivity arguments for returns to education.

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[†]Indian Institute of Management Lucknow; somdeep@iiml.ac.in

[‡]Indian Institute of Management Lucknow; jaikamal@iiml.ac.in

1 Introduction

One of the most important determinants of worker wages is the level of educational attainment of the individual concerned. This fact has been well established in the vast literature on returns to schooling (Angrist and Krueger 1991; Card 1999; Dale and Krueger 2002; Oreopoulos and Petronijevic 2013; Montenegro and Patrinos 2014). Education can lead to better labor market prospects in terms of enhanced wages primarily in two ways. First, the human capital theory would predict that education is productivity enhancing and the better earnings are just the result of increased human capital of the individual workers (Becker 1962; Mincer 1974). Second, education may just act as a signal to the potential employer in the presence of asymmetric information helping to resolve potential adverse selection issues (Spence 1973). The higher wages would then be owed to a higher correlation between unobserved skill or ability of the individual and her level of educational attainment.

While both the arguments are well grounded in theory, empirically identifying these channels apart is challenging because unobserved ability is likely to be correlated with higher wages in both these scenarios (Arteaga 2018). To be able to identify the channels individually, one would require exogenous variation either in the individual's ability to acquire human capital or the feasibility to send out a signal of quality through a diploma. In this paper, we take advantage of a law change in the Indian state of Uttar Pradesh which potentially affected just the signalling capacity of the individual without affecting the human capital endowment. In the year 1992, the government of Uttar Pradesh enacted a legislation, popularly known as the *Anti-Copying Act, 1992* (ACA) with the idea of criminalizing the use of unfair means during public examinations which was apparently rampant in the state prior to the increased vigilance due to ACA.

The ACA made all acts of using unfair means during examinations (such as leakage of questions prior to the actual tests, copying from other test-takers or books and notes during the test) cognizable non-bailable offences. As a result of the strict punishment norms, the overall percentage of students graduating high-school in the state of Uttar Pradesh fell from 57% in 1991 to 14% in 1992 (Kingdon and Muzammil 2009). Effectively, the marginal candidate who could not pass but would have passed using unfair means is not much different in terms of his signalling ability in the counterfactual compared to the individual who would pass despite the vigilance. With this new act, such marginal candidates are essentially deprived of this signal. However, the act is unlikely to have affected their overall productivity in any way. So, the labor market prospects of these marginal candidates are likely to be determined purely by productivity and not the signal of having a high school diploma. However, the labor market prospects of the ones who would have graduated from the same cohort despite the ACA would be attributable to both the signal as well as their productivity. If the mapping between wage and productivity would be identical for individuals, one could simply compare the wages of these two groups of individuals to estimate the effect of a pure signal on wage. However, it is unrealistic to assume such a uniform mapping and hence a comparison of the mean wage differential is unlikely to yield convincing estimates.

To allow for sufficient heterogeneity in individual productivity levels of workers, we modify our empirical framework as follows. We control for various household and individual characteristics including demographic controls and region-specific effects. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. An ordinary least squares (OLS) regression including all these controls and using hourly wages as a dependent variable on a dummy to identify the ones who have a high school diploma among cohorts potentially affected by the ACA would give an estimate of the impact of the diploma signal on wages. However, this may not be a perfect estimate because of other endogeneity concerns that remain. For instance, unobserved ability is still a potential omitted variable. Also, it is not clear how many among the pool of individuals who do not have the diploma would have graduated in the counterfactual. If the fraction of individuals who would not have graduated even in the counterfactual no-ACA scenario is high, then the estimate of the signalling effect from such an OLS model is likely to be biased.

To avoid such issues, we propose a reduced form difference-in-differences econometric model as our main empirical specification. Using household survey data from 2004-05 (approximately 12 years since the ACA policy was introduced), we compare the wages of cohorts potentially affected by the ACA to cohorts not affected by the ACA within Uttar Pradesh and outside.[1] The difference in long run hourly wages of the ACA cohort and the non-ACA cohort would be the potential average effect of the policy on wages, after controlling for other intrinsic differences that may exist. To account for these other differences we difference out the mean wage difference in Uttar Pradesh from these same differences inn other states and include additional controls as discussed above. The identifying assumption is that in the absence of the ACA, these cohort specific difference-in-differences would not exist. In other words, there is no obvious reason why the difference in wage of an ACA cohort compared to a non-ACA cohort would differ from Uttar Pradesh to other states, except for some policy intervention that affects these differences in Uttar Pradesh (such as the ACA).

The advantage of this empirical specification is that it allows us to get a causal estimate of the ACA program on long run wages after addressing the potential endogeneity concerns. However, it is not obvious how to identify the true effect of signalling on wages using such a framework. The estimated reduced form effects would still be confounded by both the signalling as well as productivity channels. We propose two methods of back of the envelope calculations to estimate the effect of signalling on wages. First, one may think of the ACA policy as an instrument for the high school graduation dummy in the proposed OLS model above. For relevance, it is required that ACA is strongly correlated with the probability of graduating high school. As a first stage of this proposed framework we run our difference-in-difference regressions using a variable indicating whether an individual has a diploma as the outcome. We find that ACA affects the probability of graduating adversely and also leads to a higher probability of grade repetition. To complete the two-stage least squares (2SLS) model using ACA as an instrument, one would need to calculate the predicted fitted values from the first stage and use it in the second stage regression having hourly wages as the outcome. The resultant outcome would then be the pure effect of the high school diploma on

[1] The ACA was repealed in 1993, so there is exactly one age cohort corresponding to the high school age-group in 1992 that would have been affected by the policy.

hourly wages after having instrumented the diploma indicator by the ACA policy. However, this is problematic because of two reasons.

One, such a 2SLS model requires an assumption about instrument validity. Essentially, this would mean assuming that ACA affects hourly wages only through the high school diploma indicator. This may be a strong assumption to make as we already show that ACA also affects the probability of repeating a grade. Additionally, we find that ACA affects labor force participation decisions as well as industry and occupation choice. To avoid making such a strong assumption, we do not report the 2SLS results and only focus on the reduced form estimates.[2] Two, the OLS model discussed above gives the actual effect of signalling if run only on the affected cohorts. Since the difference-in-differences model relies on cohort variation anyway, it is difficult to implement the 2SLS for the proposed OLS. To get around this issue, we execute a triple difference estimate by interacting our difference-in-difference estimator with the indicator for having graduated high school. We find that the reduced form effect of ACA on wages is much higher for the ones with the diploma compared to the one without the diploma. This incremental wage can then be attributed, in part, to the signalling component of education.

Second, the average effects on wages in the reduced form may be driven either by productivity given the potentially higher human capital endowments of the individuals who graduated in the ACA year or by experience gathered by the ones who dropped out of school in the ACA year and hence entered the labor market earlier. As a result, it is difficult to conclusively predict the magnitude of the impact of productivity over and above signalling, on hourly wages in the long run. Even with the triple difference above, it is difficult to pin-point the estimate as a pure signalling effect or a pure human capital effect because the ones who graduate in the ACA year may have higher unobserved ability in the first place which makes them successful in clearing the test. As a result, we propose to estimate the reduced form regressions for various sub-samples of individuals based on whether they have

[2]Effectively, the reduced form deflated by the first stage estimate gives an indirect least squares measure of the instrumental variables model but we leave it open to the reader to interpret the estimate and abstract away from making assumptions about validity of the exclusion restriction discussed. Also, eventually it just affects the magnitude of the true estimate and the interpretation in terms of the presence of the effect does not get diluted.

a high school diploma and whether they have ever repeated a grade. Although, one must be cautious with the interpretation of these findings because the criteria for choosing the sub-samples may themselves be affected by ACA, but nonetheless provide useful insights to answer our broader question of interest. The group of individuals from the ACA cohort who never repeated a grade and have a high school diploma must be the ones who surely succeeded in the examination in the ACA year.[3] We find large positive effects on the long term hourly wage of these individuals which maybe owed to productivity. We find smaller effects on individuals who do not have a high school diploma, suggesting that the experience effect must be smaller compared to productivity. Finally, we find very large effects on individuals who have a high school diploma but have repeated a grade (potentially including those who get the diploma after ACA was repealed) suggesting that signalling ability actually enhances labor market prospects over and above the productivity channel.

Our paper essentially contributes to the small but growing body of literature on estimating the effects of signalling and human capital on labor market outcomes (Weiss 1995; Tyler, Murnane and Willett 2000; Bedard 2001; Clark and Martorell 2014; Arteaga 2018). Our paper is however unique in two ways. First, most studies usually look at potential exogenous shocks to the human capital endowments such as changes in curriculum (Arteaga 2018) or use variation in margins of passing a given examination. In our setting, a law enforcement exogenously affected the passing percentages thereby directly affecting the signalling ability of certain individuals without affecting their overall human capital endowments. This allows us to make inferences on productivity, experience and signalling using various sub-samples. Second, to the best of our knowledge this is the first attempt to study long term labor market consequences of a high school diploma in India, particularly from the perspective of the productivity and signalling debate. Given that India is one of the largest school systems in the world with over 260 million students in schools, these findings are important in terms of sheer number of people affected and also for generalizability to other developing countries.[4]

[3] It is important to include the grade repetition criterion because we want to rule out the possibility of including individuals who have the diploma but have acquired it after ACA was repealed, potentially by retaking the examination.

[4] See here: https://www.economist.com/asia/2017/06/08/why-the-worlds-biggest-school-system-is-failing-its-pupils

2 Background

India is a federal union with 29 states and 7 union territories. In India, public examinations for secondary education are conducted by both central bodies such as Central Board of Secondary Education(CBSE) and Council for the Indian School Certificate Examination(CISCE) and state bodies of respective states. Each state has a board to conduct exams for class 10th and 12th. Majority of the population is enrolled in public schools and most of them are affiliated to state boards, although a large number of private schools are also affiliated to state boards. Thus, most students are enrolled into state board education system. Uttar Pradesh is the most populous state of the country as a result it has a large student population for public examination. So, it becomes difficult to monitor these examinations at a large scale when malpractices are prevalent. To stop unfair means in public examination, the government of Uttar Pradesh enacted an anti-copying act in 1992.

2.1 The Anti-Copying Act

Uttar Pradesh is one of the largest states in India with 199 million people according to the 2011 census, which is more than the population of Brazil, the fifth most populous country. The public examinations for secondary schools are conducted by Board of High School and Intermediate Education Uttar Pradesh. In early 1990s, the instances of mass scale copying and leakage of question papers before the exam were frequent in Uttar Pradesh. To stop these malpractices, the Uttar Pradesh Public Examination (Prevention of Unfair Means) Act -1992 [5] was introduced. This act classifies unfair means as *"the unauthorized help from any person , or from any material written , recorded or printed , in any form whatsoever, or the use of any unauthorized telephonic or wireless or electronic or other instrument or gadget"*. Another objective of the act was to stop leakage of questions prior to the examination by persons entrusted with examination related duties such as printing etc. All such unfair means were made cognizable and non-bailable offenses and police force was allowed

[5] commonly this act is known as Anti-Copying Act (ACA)

to enter in examination halls for inspection [6]. By using unfair means, students may clear tests even without studying making the quality of students passing these board examinations questionable. To make sure that the quality of students passing out is decent and to make public examinations a level-playing field, this act was considered pivotal.

The act was a major political move of it's time. It was introduced by the Bharatiya Janta Party (BJP) government led by the then chief minister Kalyan Singh [7]. In 1993, BJP government lost the state and it was attributed to the act as the other contesting parties such as Samajwadi Party (SP) promised in their manifesto to repeal this act. Fulfilling their promise, the act was repealed in 1993 by Samajwadi Party (SP) government led by the next chief minister Mulayam Singh Yadav [8].

As a result of this act, the percentage of students passing in public examinations in this state drastically came down. Compared to the 1991 examinations the pass percentage in 1992 came down to 14.7% from 52%. This drop in pass percentage was one of the sharpest (Kingdon and Muzammil, 2009). In the 1993 examinations, 25,565 students were caught when strict anti-copying measures were enforced by the BJP government as compare to 1994 when only 19,657 students were caught cheating when the law was repealed.

2.2 Conceptual Framework

The findings of our paper can be motivated by the following micro-economic models.

First , the *Job market signalling* model presents an interesting premise. The idea was introduced in a seminal paper (Spence, 1973) where hiring has been described as an investment under uncertainty and employers use signals to identify the productivity of job seekers and thus reduce the uncertainty. Education is considered as one of the most important

[6] `https://www.thenewsminute.com/politics/1582`

[7] Bhartiya Janta Party was ruling party in Uttar Pradesh when this act was enacted and Kalyan Singh was chief minister of the state

[8] `https://www.thenewsminute.com/politics/1582`

signals ; previous work experience and service records being others. The cost of education is the signalling cost and it may play an important role in the decision of job seekers to choose a level of education. The key assumption in Spence's model is "the cost of signalling is negatively correlated with productivity".

The role of education in argumenting is "human capital" is the other argument in which Education has a direct impact on productivity. The productivity increase is due to learning while acquiring education. If human capital is the only reason for increased wages i.e. a pure human capital effect, all the increase could be attributed to learning. On the other hand if education doesn't affect productivity at all but acts as a signalling device, it is considered as a pure signalling effect. While there is a vast literature which finds positive impact of education on wages, the key question remains unanswered , Does increase in wage is due to pure signalling effect or due to purely human capital effect?. Answering this question empirically by segregating signaling from human capital is difficult. However, a related question, "which of these two effects is dominant?" is relatively simple to answer and that is the key research question of our paper.

Second, the neoclassical *model of labor-leisure choice* provides another interesting analytical framework on which we can base our empirical exercise. If individuals have a predefined utility function , then based on their preferences and interpersonal differences , one could model their "taste for work". The consumption of leisure and consumption of goods by earning money from working is limited by a budget constraint as total available time is limited and "non-labor income" is also limited. The optimal allocation to leisure in this trade-off between leisure and labor is obtained from the standard utility maximization conditions. This model can help us in predicting effect of wage changes on equilibrium labor force participation decision and on the optimal choice of hours of work conditional on participation.

The comparative statics of this model allowing for the changes in the wage may predict the existence of a *backward-bending* labor supply curve. There are two possibilities: in the first case optimal leisure declines as substitution effect dominates the income effect and in the second one income effect dominates leading to increase in leisure. In our paper, we try to empirically find the dominant effect by studying the partial equilibrium effect of a shock that changes wages.

This model also helps in finding the optimal condition for participation in labor market using the concept of reservation wages. The reservation wage depends on the utility function and a person will not work if the market wage is less than her reservation wage. Thus, a high reservation wage suggests that the individual is less likely to join labor market.

Third, there exists a strand of literature which deals with relationship between productivity and wages (Lazear, 1981 and Lazear, 2018). According to the human capital models of wage growth , the wage growth should be proportional to productivity once education and experience is controlled for, but there can be differences because of discrimination wage. Hellerstein et al. (1999) argue that *"Without independent measures of worker productivity, it is difficult to determine whether wage differentials associated with worker characteristics reflect productivity differentials or some other factor, such as discrimination"*. As we don't have any such independent measure, we have assumed the human capital models of wage growth to be working in our case.

3 Empirical Framework

The ideal way to estimate the effect of signaling and human capital separately is to randomly assign students into three groups. First, a group with a high school diploma (signal) without imparting any education at all. Second, a group with education without awarding of diploma and the last group with neither education nor diploma. In presence of such a hypothetical experiment, one could potentially compare group 1 to group 3 to estimate true effect of a signal. Similarly, a comparison of group 2 with group 3 would give the true effect of human capital in isolation. However, conducting such experiments is not only infeasible but also has ethical concerns. Hence, the second best option is to exploit quasi-experimental variation provided by natural experiments such as the ACA.

In early attempts to test presence of signaling, Liu and Wong (1982) find that certificate years have more returns to schooling than non-certificate years which provides some anecdotal evidence of the presence of signaling effect. In other such descriptive work, Miller and Volker (1984) find evidence against human capital argument as science graduates earn similar wages in science and non-science jobs. Lang and Kropp (1986) also find signaling effects by exploiting compulsory schooling laws.

More recent attempts try to identify the causal linkages, such as Tyler et al. (2000) exploit interstate variations in passing standards for GED(General Educational Development). They compare wages of individuals from high standard states and low standard states. If scores in exams are true estimates of human capital, students scoring same marks should have similar wage. Due to variations in passing standards, even if two individuals have same score, the individual belonging to high passing standard state may not get GED certificate. Using this methodology, they find GED have signaling value. Clark and Martorell (2014) use a regression discontinuity approach to compare the earnings of those who could barely pass and those who could just pass and find very little signaling value of a high school diploma. Arteaga (2018) exploits coursework curriculum reform to reject a pure signaling model and find that human capital plays an important role in wage determination.

In this paper, we exploit variation from the ACA which has potential to affect individual's ability to signal. We propose a difference-in-difference regression framework to get around issues of potential endogeneity arising from selection and unobserved heterogeneity.

3.1 Identification Strategy

We propose an identification strategy that relies on plausible exogenous variation in individuals affected by ACA to find its causal effects. Apart from the state dimension which provides variation in the exposure to policy because of residence of individual as the policy was intended only for Uttar Pradesh, we use other dimension as age cohort affected. ACA was enacted in 1992 and all individuals who were to give public examinations were affected. The typical age group of individuals in secondary education is 15 to 18. As we are interested in long term labor market outcomes, we have looked at the 2004-2005 data set and as reported in Table 1, individuals who were 15 years old in 1992 will be 27 years old in 2004-05 and similarly we can find the age in 2004-05 for other affected individuals. We use an interaction of these dimensions to identify the effect of the policy.

We define variable UP as a dummy variable which takes value 1 if an individual is resident of Uttar Pradesh and zero otherwise. We define another variable *agecohort* as dummy variable such that this takes the value 1 if the individual belongs to the age group for whom the ACA was intended , i.e. if age of an individual is between 27 to 30 and zero otherwise. We use this framework to run a regression for individual 'i':

$$Y_i = \alpha + \beta_1 \cdot UP_i + \beta_2 \cdot agecohort_i + \beta_3 \cdot (UP_i \cdot agecohort_i) + \gamma_i \cdot X_i + \epsilon_i, \qquad (1)$$

The parameter of interest is β_3, which captures the true effect of ACA on outcomes Y. In our model Y_i is either one of the labor market outcomes such as log hourly wage, hours worked, occupation choice and industry choice or one of the educational outcomes such as AboveTen, Repeater. We define $AboveTen$ as a dummy variable which takes 1 if an individual has earned high school diploma and zero otherwise. In addition, we define *Repeater* as a dummy variable which takes 1 if an individual has ever repeated any grade and zero otherwise. X_i are control variables that include total number of persons in household, total children in household, highest level of education for any adult in household and presence of a literate member in household.

Interpreting the estimated regression coefficient in this framework gives us the difference between the individuals who were exposed to the policy and those who were not. The critical identifying assumption is that this outcome would not have been different for unaffected group had there been no ACA.

3.2 Data

We use the nationally representative dataset IHDS-1 (Indian Human Development Survey - 2005) for our analysis . The data was collected in year 2004-05 for 41,554 households in 1,504 villages and 970 urban neighborhoods across India. It is a very rich data set which provides information regarding various household and individual characteristics.
For our analysis , we have used information on labor market outcomes such as wage rate , hours worked and occupation etc. and also on various demographic indicators such as age, gender , number of children in household, highest qualified individual in household and percentage of literate in household etc. The timing of collection of data gives us an opportunity to look at a long term effects of ACA program as the data was collected in 2004-05 and the policy was introduced in 1992.

The summary statistics of key variables is shown in Table 2. Uttar Pradesh roughly represents 10% of the entire sample. Around 16% of the individuals have repeated at least one grade throughout their education and 20% of the individuals have earned a high school diploma. There is roughly similar representation of gender in the data set as the percentage of males is slightly above 50. Average age of individuals in sample is around 27. Number of persons in household averages to 6.38 and number of children averages to 2.20. The average highest level of adult education is 7.82 years where average highest level of education for female and male is 4.79 and 7.45 respectively. On an average, 81% households have at least one member who is literate. The average hourly wage is 12.83 INR for full sample and notable from the table is that hourly wage of out of school sample is almost half of in-school sample. Individuals work for around 8 hours a day and out of school sample works little less than in-school sample.

4 Results

In this section we start with the discussion of the effects of ACA on educational outcomes and labor market outcomes and next we supplement our analysis with falsification exercise. Afterward, we present heterogeneous effects and effect of ACA on industry and occupation choice.

4.1 Main Results

ACA was enacted to curb the unfair means such as leakage of questions prior to the actual tests and copying from other test-takers or books and notes during the test. So, it has the potential to affect the low ability individuals who pass the public examination of high-school using unfair means, in the counterfactual. We are interested in knowing how the policy affected probability of graduating high school. For this purpose, we create a dummy variable *aboveten*, which takes the value of 1 if the individual has a high school diploma and zero otherwise. We estimate the effect of ACA on pass probability using equation 1 and we report the results in Table 3 . The specification (1) of Table 3 is the baseline model without any control variables or state fixed effects. We find that the population potentially affected by the policy is less likely to have a high-school diploma.The counterfactual implies that in the absence of the policy, more students would have cleared examination to get the diploma. This is consistent with the presence of prevalent mass copying and other malpractices used to clear these examinations in absence of ACA. Our model is not sensitive to additional controls and state FE, as it is evident from column (2) and (3).

Further in Table 3 , we test the effect of ACA on probability of repeating. The impact of ACA is positive on probability of repeating any grade including grade ten. The results are consistent with the expectations that in the presence of stricter penalties for using unfair means in examinations, there would be less students who could pass. On an average, the affected individuals by ACA are around 4-5% more likely to repeat any grade. The results are not sensitive to specification and including controls and fixed effects doesn't change the magnitude or direction compared to the baseline as evident from column 4-6 of the Table 3.

Additionally, we are interested in capturing the long term labor market consequences of this exogenous shock. Table 4 presents the results for the effect of ACA on labor force participation. The coefficient in column (3) of the table is negative which suggest that in absence of such a policy more people with have joined labor force. On an average, the affected individuals are 2.5% less likely to be part of labor force.

As the results of Table 4 suggests,in the absence of the policy, the affected individuals would have worked 0.19 hours less than unaffected cohort. The possible reasons for this are explained in next paragraph. The key finding of our paper is reported in Table 5, the column (3) reports an average increase of 3.67 rupees in hourly wage. Thus, the affected cohort has more wage rate as compared to control cohort which means , in absence of ACA, affected cohort might have earned less. This suggests that those who have earned a high school diploma in presence of stricter vigilance are earning more.

As reported earlier, for individuals affected by ACA, hourly wages are higher and the labor force participation is lower. One possible explanation for this to happen is that in absence of ACA there was disguised employment. In the counterfactual, individuals might not be working at full capacity and so they will be willing to accept a low wage to work. Other way to look at it is with the ACA , now only quality students are able to graduate high school and they are able to get more wage and those who are unable to graduate prefer to stay out of labor market.

The relationship between hours worked and the hourly wage is discussed in conceptual framework section. There are two possible effects. In first case if income effect is dominant, people work less for an increase in wage rate and in second case if substitution effect dominates people work more when wage rate increases. It is evident from the results of Table 4 and Table 5 that both number of hours worked and hourly wage is increasing i.e. the substitution effect is dominant in our case. The backward bending supply curve, graphical representation of individual's supply curve, shows that initially the hours worked increases with the increase in wage rate and then after a point the curves bend backward i.e. the hours worked decrease with increase in wage. In our case, most individuals are in positively sloped part of backward bending supply curve where hours worked increases with hourly wage rate.

In addition to difference-in-difference estimates, we performed a triple difference exercise where we interacted the difference-in-difference estimator with the indicator variable for having graduated high school. The triple estimates reported in Table 6 suggest that the reduced form effect of ACA on wages is much higher for the ones with the diploma compared to the one without the diploma. This incremental wage can then be attributed, in part, to the signalling component of education.

4.2 Falsification

Quasi- experimental methods are better than OLS estimates for causal interpretation nevertheless even with quasi-experimental methods concerns of not able to estimate true causal effect remain. To address this issue, we performed a falsification exercise. As the policy was intended for those who appeared for public exam , the regression equation (1) should give insignificant results for those who are in treated age cohort and who are resident of Uttar Pradesh but they are out of school i.e. the estimates produced by our identification strategy for out-of-school sample should be insignificant. The results for the falsification exercise is shown in Table 7 . The first three columns of the table 7 suggest that the policy didn't affect out-of-school sample's probability of labor force participation. For $hoursworked$ this falsification exercise doesn't seem to work. For our main variable of interest , $hourlywage$, the falsification exercise suggests that the hourly wage for out-of-school cohort is not affected by the policy as the coefficient of interest is insignificant.

4.3 Do the effects vary by demographics?

In this section, we divided the data into various sub-samples based on demographic indicators and estimated the regression equation 1. The advantage of estimates for sub-samples over full sample is that sub sample analysis gives a detailed picture as opposed to full sample where average effects are estimated. For this analysis, we also looked at various sub samples based on gender, residence status , caste and passing status. The effect of ACA on labor market outcomes such as working status, hours worked and hourly wage for different sub-samples are discussed below :

First, we divide the data based on gender and the results are reported in figure 1. As both hourly wage and hours worked is more for affected age cohorts of both male and female, we can conclude that substitution effect is dominating for both genders. Also, the effect size of ACA on hourly wage for female more when compared to male and the same is true for hours worked as well which suggest that the substitution effect is even more for female. Based on working status and hourly wage results , in the absence of ACA, we could have witnessed presence of disguised employment for males whereas no such conclusion can be drawn about females. The effect of ACA on labor force participation is unclear for females.
Second, we divide the data based on residence status and the results are reported in figure 2. Hourly wages is more for affected age cohorts of both rural and urban population and the effect size is more for urban population. Hours worked is more for affected rural population, whereas hours worked is not statistically different from zero for urban population and thus we find substitution effect in rural population but we cannot confirm such effects for urban population. Based on working status and hourly wage results , in the absence of ACA, we could have witnessed presence of disguised employment for rural population whereas no such conclusion can be drawn about urban population. The effect of ACA on labor force

participation is negative for rural population and unclear for urban population.

Third, we divide the data based on caste and the results are reported in figure 3. The effect of ACA on hourly wage is positive for all castes except ST where no such effect is found and effect of ACA on hours worked is positive for all castes expect ST where effect is not precisely estimated. This suggest presence of substitution effect for Brahmin, OBC and SC but neither substitution nor income effect can be confirmed for ST. Effect of ACA on labor force participation is not statistically signification for all caste except ST. In case of ST, the cohort affected by ACA , has more probability of labor force participation compared to those who were not affected by ACA.

Lastly, we divide the data based on passing status and the results are reported in figure 4. As we don't have information on the passing status in the exam conducted in 1992-93 for individuals who were affected by policy, we use above defined dummy variables *aboveten* and *repeater* to divide sub-samples. Based on the two dummy variables, among all possible four combinations, we are interested in two such sub-samples : one who couldn't pass class ten ever and others who passed class ten in first attempt. If a person has highest qualification more than or equal to ten and he has never repeated any grade i.e. that person has passed class ten in his first attempt. All such individuals of affected age cohort can be best representative of individuals who passed the exam even after the strict invigilation. They are important because they definitely passed exam in presence of ACA. The second sub-sample is those who have highest qualification as class 9 and they have repeated at least one grade in their lifetime. They are the individuals who couldn't pass class ten in all the attempts that they have taken. This sample includes both who have attempted class ten and could not clear and those who didn't attempt class ten ever. The results for both the samples is shown in figure 4. The effect of ACA on hourly wage is almost double for those who could pass in first attempt when compared to those who could not pass even after repeating.

We have also reported the sub sample analysis for other outcome variables such as probability of passing ten and probability of repeating any grade including high school in the Appendix.

4.4 Industry and Occupation Choice

In this section, we used dummy variables for each occupation and used it as dependent variable of regression equation 1. The occupation choice dummy variable takes value 1 if the individual is working for that occupation, otherwise it takes zero. Similarly, we have created dummy variable for each industry. The estimated coefficients corresponding to ACA can be interpreted as effect of ACA on probability of choosing a particular occupation or industry. The effect of ACA on selected occupations are reported in table 9 which suggests that affected age cohort is less likely to join clerk , cook, waiter , agricultural laborer, Tobacco worker, Tailor, Assembler and loader whereas they are more likely to join service worker , Food worker, Painter , General Labor and Construction worker. The results for effect of ACA on Industry choices is shown in table 10 which suggest that affected cohort is less likely to choose agriculture, manufacturing , transport and financial sector whereas they are more likely to choose community, social and personal services.

5 Robustness

In this section we check robustness of results discussed earlier. Firstly, we restrict the sample to only 10 states which include Uttar Pradesh and other 9 states that directly share boundary with Uttar Pradesh. Secondly, we want to perform randomization. In this case one of those 10 states will be selected randomly as treated state and remaining states will be treated as controlled state.

5.1 Restricted Sample

When we restrict our sample to the states that share boundary with Uttar Pradesh, the results are intact and they are reported in table 8. The reason for restricting the sample to only ten states is that all the states that share boundary with Uttar Pradesh have more similarity in culture, economic conditions and climate as opposed to the states that are geographically far away. As shown in table 8, the effect of ACA on working status is negative, on hours worked is positive and on hourly wage is positive. The direction and magnitude of estimates are similar to our main results and hence we find our results are robust if we restrain our analysis to ten states only.

5.2 Test of Exact Randomization

The key variable of interest for our analysis is “hourly wage”. We have claimed that those who were affected by the policy their hourly wage is increase by 3.85 rupees. To test for robustness of this, we use test of exact randomization similar to Bharadwaj et al. (2014) and we change the treated state each time and try to capture the effect. It is like considering that “had the policy been implemented in one randomly selected state and not other states, what would have been impact?”. The results of this analysis are reported in figure 5. Apart from Uttar Pradesh, only one other state , if taken as policy state, has similar result and for all remaining states , if they are taken as policy state, either the coefficient is insignificant or the coefficient is negative. Thus, our results are robust to randomization.

6 Conclusions

In this paper, we looked at a reform in the Indian State of Uttar Pradesh, ACA, which aims to stop the use of unfair means in public examinations by making use of unfair means cognizable and non-bailable offense. Using data on educational outcomes, we find the the presence of ACA reduces the probability of graduating high school and increases the probability of repeating a grade. Using labor market outcome data, we find that hourly wages have gone up for treated cohort and they are less likely to join labor force and conditional on joining , they work for more number of hours. As the individuals who were affected by ACA work for more number of hours and earn more wages, we empirically show that individuals are on positively sloped part of backward-bending supply curve due to presence of substitution effect in labor supply.

The individuals who could graduate high school even with strict surveillance have much higher wage supports the human capital and productivity arguments for returns to schooling. On the other hand, we cannot rule out signalling as triple difference estimates show that hourly wages are higher for the ones who have diploma and the rise in wages can partly be attributed to signalling.

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Appendix

Effect of ACA on probability of passing ten

The figure 6 shows effect of ACA on probability of passing ten. It is clear from the figure that the effect of ACA on passing ten is negative for male whereas for female effect is statistically insignificant. Also, the effect of ACA on probability of passing ten for urban population is negative whereas for rural population no clear effect is evident.

Effect of ACA on probability of repeating

The figure 7 suggests that both male and female have higher probability of repeating when they are compared to those who were not exposed to ACA . Similarly, with ACA into force, both rural and urban affected cohorts have higher probability of repeating. This trend is not clear when we look at sub-samples based on caste and religion.

Tables and Figures

Table 1: ***Age-cohort***

Age in 1992-93	15	16	17	18	19	20	21	22
Age in 2004-05	27	28	29	30	31	32	33	34
Treated/ Control	T	T	T	T	C	C	C	C

Table 2: ***Summary Statistics***

	Full Sample		Out school		In School	
	Age 27 to 34	All Age	Age 27 to 34	All Age	Age 27 to 34	All Age
Percent Repeater	21.96	15.98	-	-	22.13	16.77
Percent Above 10th Standard	34.25	19.46	-	-	47.39	30.65
Percent UP Population	8.90	9.95	13.77	12.645	7.04	8.4
Percent Male	49.52	50.89	28.66	40.35	57.53	56.96
Age	30.20	27.35	30.35	28.35	30.14	26.77
Number of persons in household	6.42	6.38	6.55	6.62	6.37	6.25
Number of children in household	2.43	2.20	3.01	2.54	2.2	1.99
Highest Adult (21+) education	8.69	7.82	3.78	5.48	10.58	9.16
Highest Female(21+) education	5.86	4.79	0.82	2.59	7.81	6.05
Highest Male(21+) education	8.21	7.45	3.54	5.21	9.98	8.73
Percent Literate (Any member in family)	86.23	81.26	51.89	64.17	99.42	91.09
Log(wage)	9.46	9.41	8.78	8.79	9.77	9.76
Hours Worked	8.03	7.97	7.89	7.85	8.09	8.03
Hourly wage	11.95	12.83	6.26	6.78	14.5	16.31

Table 3: ***Effect of ACA on Passing ten and Repeating***

	Above Ten			Repeat		
	(1)	(2)	(3)	(4)	(5)	(6)
ACA	-0.0576***	-0.0314***	-0.0310***	0.0545***	0.0496***	0.0463***
	(0.00830)	(0.00464)	(0.00408)	(0.00605)	(0.00538)	(0.00488)
Observations	17,526	17,095	17,095	17,407	17,093	17,093
R-squared	0.000	0.651	0.656	0.000	0.012	0.079
state FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dummy variable Aboveten is 1 when an individual has at least ten as his highest educational qualification and repeat is 1 if an individual has repeated at least one grade in his lifetime. The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) and (6) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to ACA captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** $p<0.01$ **$p<0.05$ *$p<0.1$

Table 4: ***Effect of ACA on Working Status and Hours Worked***

	Working Status			Hours Worked		
	(1)	(2)	(3)	(4)	(5)	(6)
ACA	-0.00361	-0.0253**	-0.0248***	0.262***	0.189***	0.190***
	(0.0114)	(0.00965)	(0.00830)	(0.0441)	(0.0468)	(0.0423)
Observations	17,526	17,095	17,095	6,992	6,816	6,816
R-squared	0.003	0.217	0.237	0.001	0.058	0.081
state FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dummy variable working status is 1 when an individual is in labor force and hours worked is number of hours worked per day. The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) and (6) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to ACA captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** p<0.01 **p<0.05 *p<0.1

Table 5: ***Effect of ACA on Hourly Wage***

	Hourly Wage		
	(1)	(2)	(3)
ACA	3.407***	3.350***	3.467***
	(0.460)	(0.373)	(0.366)
Observations	6,992	6,816	6,816
R-squared	0.008	0.226	0.265
state FE	No	No	Yes
Controls	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dependent variable hourly wage is average rupees earned for one hour of work . The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to ACA captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** p<0.01 **p<0.05 *p<0.1

Table 6: ***Triple Difference Estimates***

	(1)	(2)	(3)
Triple	4.519***	4.828***	4.914***
	(1.015)	(0.917)	(0.907)
Observations	6,992	6,816	6,816
R-squared	0.124	0.229	0.268
State Fixed Effects	No	No	Yes
Controls	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dependent variable is hourly wage i.e. average rupees earned for one hour of work . The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to Triple captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** p<0.01 **p<0.05 *p<0.1

Table 7: ***Effect of ACA on Working Status , Hours Worked and Hourly Wage - Out of school***

	Working Status			Hours Worked			Hourly Wage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACA	-0.0257*	-0.0254	-0.0221	0.607***	0.503***	0.486***	0.0535	-0.0497	-0.00770
	(0.0131)	(0.0157)	(0.0141)	(0.0646)	(0.0559)	(0.0585)	(0.147)	(0.175)	(0.155)
Observations	6,724	6,524	6,524	3,132	3,025	3,025	3,131	3,024	3,024
R-squared	0.022	0.220	0.310	0.004	0.066	0.107	0.002	0.149	0.254
state FE	No	No	Yes	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dependent variables are working status, hours worked and hourly wage. Working status is a dummy variable and it takes value 1 when an individual is in labor force and hours worked is number of hours worked per day and hourly wage is average rupees earned for one hour of work . The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) , (6) and (9) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to ACA captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** p<0.01 **p<0.05 *p<0.1

Table 8: ***Effect of ACA on Working Status , Hours Worked and Hourly Wage - Inschool and 9 control states***

	Working Status			Hours Worked			Hourly Wage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ACA	-0.00796	-0.0347*	-0.0359**	0.174**	0.0825	0.0961*	3.488***	3.471***	3.846***
	(0.0172)	(0.0163)	(0.0150)	(0.0559)	(0.0532)	(0.0501)	(0.595)	(0.571)	(0.639)
Observations	6,465	6,288	6,288	2,532	2,459	2,459	2,532	2,459	2,459
R-squared	0.008	0.239	0.252	0.003	0.056	0.064	0.009	0.236	0.276
state FE	No	No	Yes	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes: We have used IHDS (Indian Human Developmet Survey) dataset to estimate results. The dependent variables are working status, hours worked and hourly wage. Working status is a dummy variable and it takes value 1 when an individual is in labor force and hours worked is number of hours worked per day and hourly wage is average rupees earned for one hour of work . The regression has various controls such as household and individual characteristics including demographic variables. Additionally, we use the actual years of education and age in our regressions to control for potential heterogeneity in human capital endowments. Specification (3) , (6) and (9) has used state fixed effects. The data set is restricted to the individuals who are at least 27 and at most 34 and the treated age cohort is individuals that are at least 27 and at most 30. The coefficient corresponding to ACA captures the true effect of policy (Anti-Copying Act) in difference-in-difference setup. Robust Standard Errors in parentheses. *** p<0.01 **p<0.05 *p<0.1

Table 9: ***Effect of ACA on Occupation Choice -Selected Occupations***

	(1)	(2)	(3)
Engineers	-0.000579	-0.000900	-0.000724
	(0.000942)	(0.000967)	(0.000968)
Nursing	0.00106	0.00102	0.00124
	(0.000840)	(0.000829)	(0.000863)
Teachers	-0.00536	-0.00222	-0.00184
	(0.00318)	(0.00302)	(0.00300)
Clerical nec	-0.00438**	-0.00683***	-0.00599***
	(0.00201)	(0.00213)	(0.00198)
Sales, shop	-0.00121	-0.00213	-0.00198
	(0.00215)	(0.00205)	(0.00200)
Cooks/waiters	-0.00465***	-0.00523***	-0.00515***
	(0.000991)	(0.000924)	(0.000965)
Sweepers	0.00699***	0.00642***	0.00649***
	(0.000993)	(0.000989)	(0.000990)
Police	-0.00126	-0.00172	-0.00174
	(0.00146)	(0.00148)	(0.00157)
Service nec	0.00376***	0.00450***	0.00437***
	(0.000994)	(0.00105)	(0.00107)
Ag labour	-0.0138**	-0.0181***	-0.0193***
	(0.00629)	(0.00546)	(0.00472)
Textile	-0.0130***	-0.0122***	-0.0123***
	(0.00127)	(0.00102)	(0.000997)
Food	0.00781***	0.00741***	0.00744***
	(0.000912)	(0.000947)	(0.000914)
Tobacco	-0.00244**	-0.00252**	-0.00191**
	(0.000926)	(0.000969)	(0.000916)
Tailors	-0.0108***	-0.00747***	-0.00738***
	(0.00102)	(0.00102)	(0.000949)
Carpenters	0.000119	-0.000968	-0.00112
	(0.00130)	(0.00126)	(0.00131)
Assemblers	-0.00216*	-0.00327**	-0.00331**
	(0.00120)	(0.00124)	(0.00124)
Electrical	-0.00212	-0.00317*	-0.00305*
	(0.00146)	(0.00158)	(0.00163)
Plumbers/welders	0.000560	0.000343	0.000268
	(0.00122)	(0.00121)	(0.00119)
Painters	0.00281***	0.00222**	0.00208**
	(0.000708)	(0.000819)	(0.000840)
Construction	0.0120***	0.00664***	0.00644***
	(0.00256)	(0.00216)	(0.00224)
Loaders	-0.00655***	-0.00741***	-0.00761***
	(0.00135)	(0.00137)	(0.00132)
Drivers	0.00330	-0.000423	-8.94e-05
	(0.00231)	(0.00265)	(0.00277)
Labour nec	0.0113***	0.00919***	0.00886***
	(0.00229)	(0.00259)	(0.00267)
State Fixed Effects	No	No	Yes
Controls	No	Yes	Yes

Table 10: ***Effect of ACA on Industry Choice***

	(1)	(2)	(3)
Agriculture, Hunting, Forestry And Fishing	-0.01000	-0.0152*	-0.0164**
	(0.00831)	(0.00758)	(0.00655)
Mining And Quarrying	0.00218	0.00172	0.00159
	(0.00152)	(0.00151)	(0.00146)
Manufacturing	-0.00687	-0.0103**	-0.0105**
	(0.00468)	(0.00461)	(0.00438)
Electricity, Gas And Water	5.32e-05	-0.000998	-0.000679
	(0.00151)	(0.00147)	(0.00144)
Construction	0.0120***	0.00530*	0.00502
	(0.00302)	(0.00312)	(0.00323)
Wholesale, Retail Trade And Restaurants, Hotels	-0.00110	-0.00319	-0.00286
	(0.00290)	(0.00286)	(0.00278)
Transport, Storage And Communication	-0.00751**	-0.0124***	-0.0123***
	(0.00308)	(0.00355)	(0.00373)
Financing, Insurance, Real Estate & Business Services	-0.00221	-0.00300**	-0.00296**
	(0.00133)	(0.00130)	(0.00131)
Community, Social And Personal Services	0.0148**	0.0198***	0.0212***
	(0.00629)	(0.00587)	(0.00582)
State Fixed Effects	No	No	Yes
Controls	No	Yes	Yes

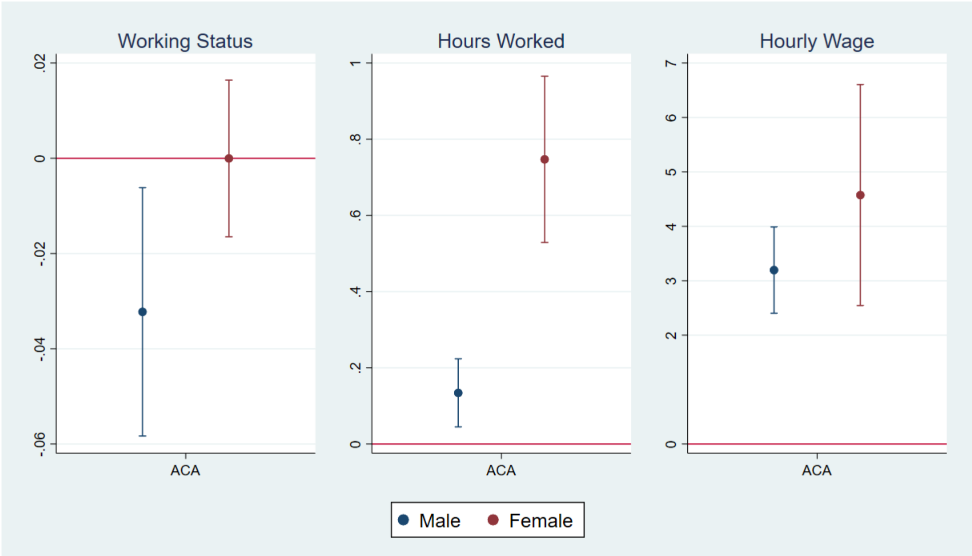

Figure 1: ***Gender-wise effect of ACA on labor market outcomes***

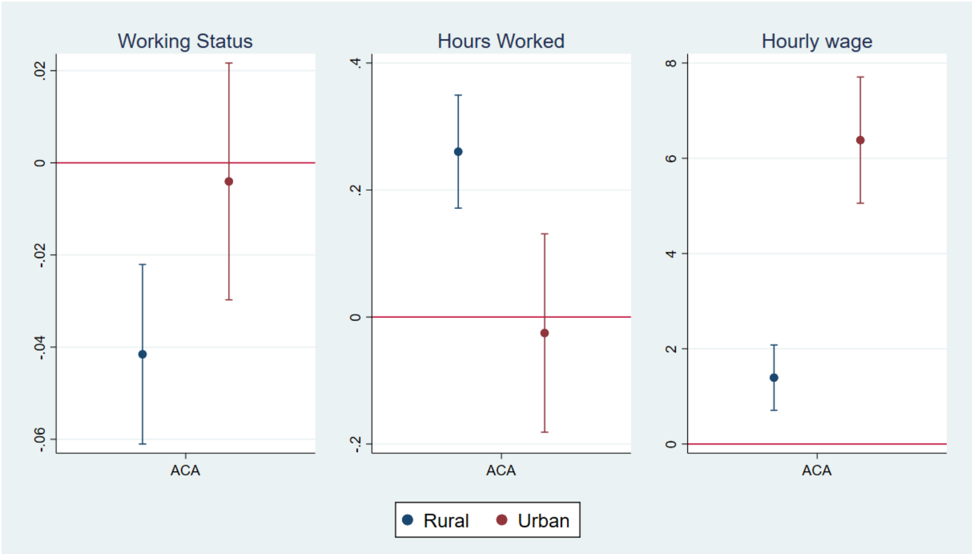

Figure 2: ***Residence-wise effect of ACA on labor market outcomes***

Figure 3: ***Caste-wise effect of ACA on on labor market outcomes***

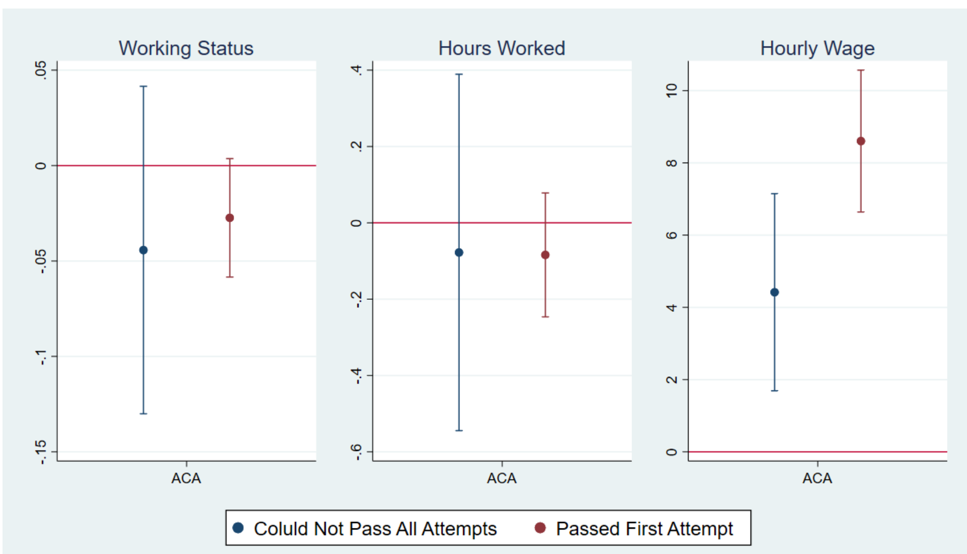

Figure 4: ***Effect of ACA***

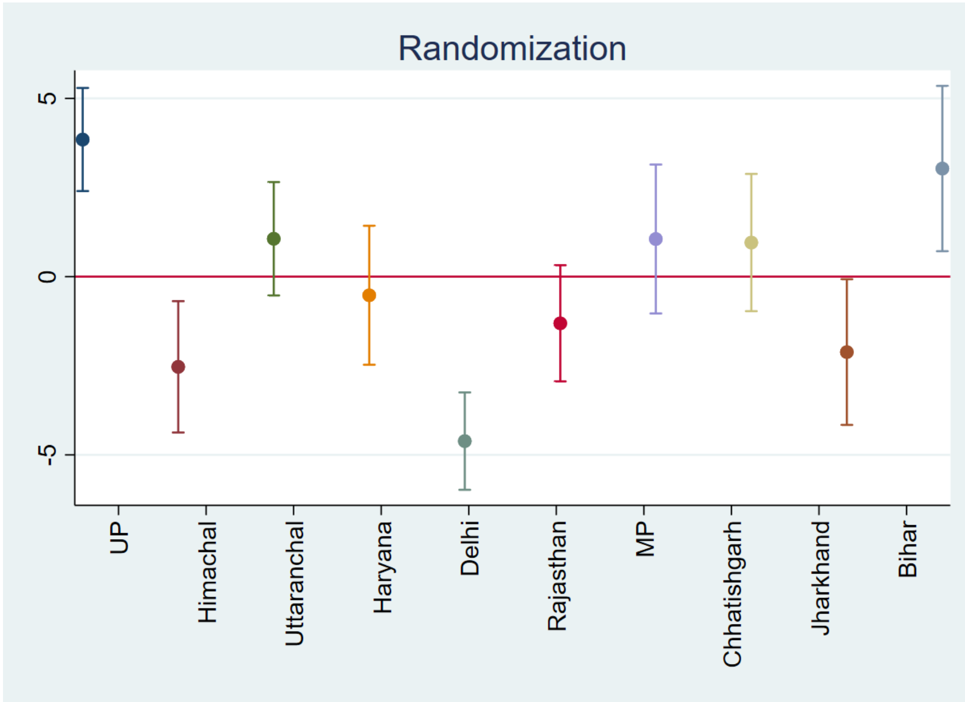

Figure 5: ***Randomization Summary - 9 possible cases***

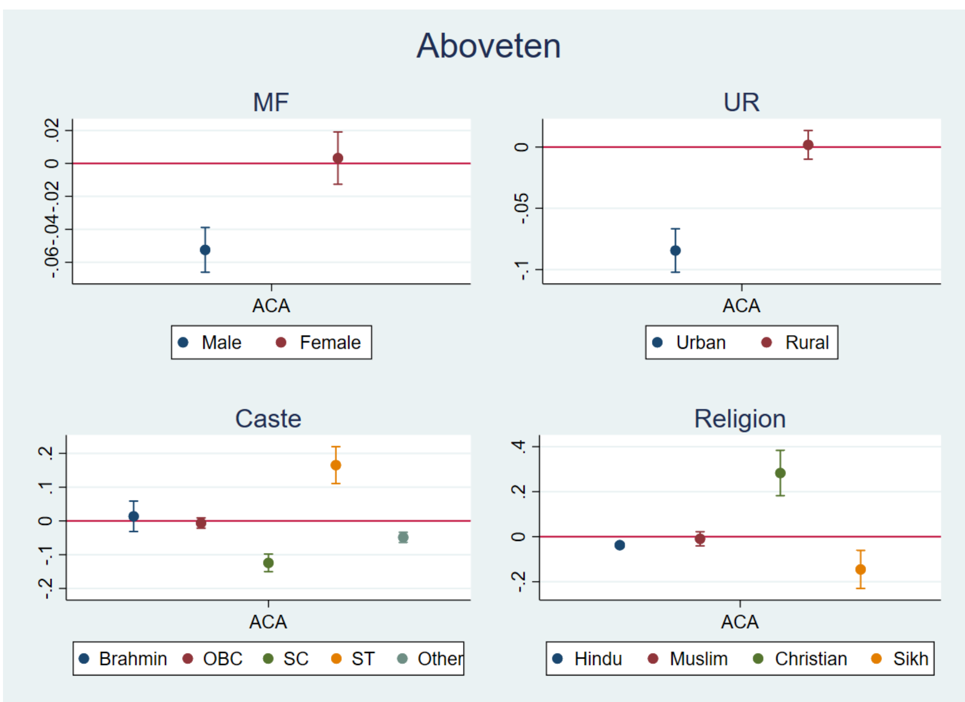

Figure 6: ***Effect of ACA on Graduating High School***

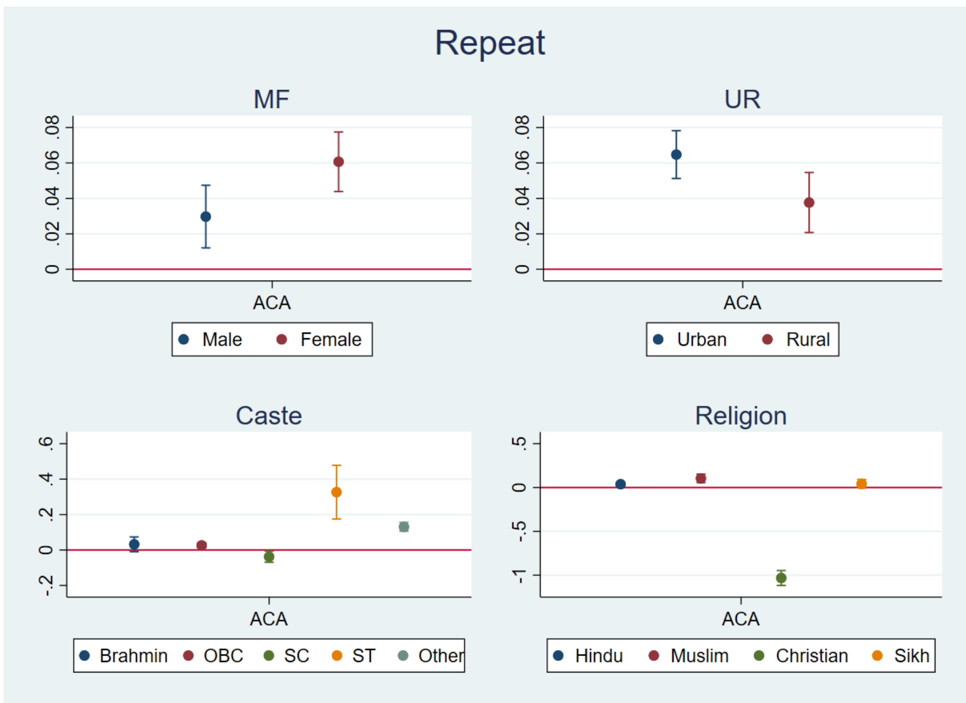

Figure 7: ***Effect of ACA on Repeating***