***Draft-do not quote or cite**

Conditional Cash Transfer for Secondary Education: Impact Assessment of the Kanyashree Program in West Bengal

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Abstract

Over the past two decades, conditional cash transfer programmes have gained importance to improve schooling outcomes and delay female child marriage. This paper evaluates the impact of one of such programme implemented in West Bengal (WB) since 2013 known as the Kanyashree Prakalpya (KP) on female schooling outcomes including enrollment and learning outcomes. Using data from Annual Status of Education (ASER) from 2011 to 2018, we employ double difference, triple difference and synthetic control methods to assess the impact of KP on female enrollment and learning outcomes. The findings indicate controlling for household factors as well as village level infrastructure, KP has been able to increase female enrollment significantly. However, no significant impact in learning outcomes is found and thus we couldn't establish any connection between enrollment and educational attainment. We use DISE data to study school infrastructure and found them to be inadequate in WB possibly explaining the lack of gains in learning outcomes.

Key words: Kanyashree, Conditional Cash Transfer, Triple Difference, Synthetic Control

1. Introduction

In low and middle income countries, a significant portion of the female are denied the opportunity to participate in secondary education. The lack of female participation involves substantial economic and social costs: a World Bank study of 100 countries demonstrated that increasing the secondary education of girls by 1 per cent might be associated with 0.3 per cent in increase in annual per capita income (UNGEI, 2014). Social benefits of female education also

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surfaces in terms of reduced fertility rate and reducing the phenomenon of child marriage. In developing countries propensity to invest in human capital for girl child is low. This is because while primary education in public institutions is subsidized, secondary education involves costs. At the same time cultural bias against women might act as additional constraint on female education. Some households might attach low priorities to female education particularly at the secondary level.

In such situation, Conditional Cash Transfers (CCT) have found widespread use in incentivizing households to compensate for the opportunity cost of enrolling girl child and continuing their education who would otherwise be married at an early age[1]. Getting the daughters married at a later age involves more costs on their upkeep and can enhance dowry. This could happen especially if the pre-existing social norms tend to relate the quality of the bride with her age. Thus, besides augmenting women empowerment, CCT programs for female education is also seen as an instrument to halt or delay the process of child marriage. Child marriage has been found to be associated with increased risk for sexually transmitted diseases, cervical cancer, malaria, and obstetric fistulas (Nour, 2006).

In its canonical form CCT program for female education provides monetary incentives for girls that continue secondary education while remaining unmarried till she attains 18 years of age. The incidence of CCT programs for initiating secondary education among girl child is widespread in Latin American countries like *Bolsa Familia* in Brazil and *PROGRESSA* in Mexico but over time it's being increasingly implemented in other parts of the world particularly South Asia where the prevalence of under-age marriage of girls is highest. India is a case in

[1] CCTs generally have three common program objectives , viz., human capital formation, alleviation of poverty and provision of safety net during economic crisis.

point where there is high incidence of child marriage. With affirmative policies like passage of Prohibition of Child Marriage Act (2006) the incidence of child marriage has declined from 54% in 1992-93 to 27% in 2016[2] but still it is more prevalent in rural areas (48%) coupled with high dropout rates in secondary classes. Thus, the extent to which CCT programs might be effective in India is an important policy concern especially as promoting gender equality in education is one of the Sustainable Development Goals (SDG) that needs to be met by 2030. In this context our paper contributes to the policy debate by analysing the impact of one of the most prominent CCT program designed to encourage secondary education for girl child –*Kanyashree Paraklapa* (henceforth KP) in West Bengal an eastern state in India.

As per Census 2011, close to 8% of the females are married before 18 years of age in West Bengal against the national average of 3.7% and the District Level Household Survey(DHLS) 2012-13 documented that mean years of schooling for women is also below national average. In West Bengal KP was introduced in 2013 that targets adolescent girls of 13-19 years of age and offers two tier scholarships of INR 750 (USD 10.56) and a lump-sum grant of INR 25000 (USD 352) upon attaining the age of 18 and "conditional" on the girl continuing her studies and remaining unmarried at that point of time[3]. In 2017, KP secured the first place in the United Nations Public Service Award but till date there had been no rigorous assessment of its impact on female educational outcome in West Bengal.

Though CCT programs in education have been encouraged as an instrument to correct for "incomplete altruism" between parents and children where the former may discount the returns from investment in human capital more heavily than optimal. For instance in 'patrilocal'

[2] https://unicef.in/Whatwedo/30/Child-Marriage
[3] https://www.theigc.org/project/kanyashree-prakalpa-in-west-bengal-india-justification-and-evaluation/ (accessed on September 15, 2019)

societies parents might underinvest in girl's schooling as compared to their male counterpart girls are less likely to devote more time for their parents as they move to their husbands' home after marriage (Fiszbein & Schady, 2009). However, studies have also noted substantial opportunity costs associated with CCT in education. These can arise in two ways: first if the educational amenities are inadequate and teaching qualities are low providing conditional cash incentives are unlikely to go beyond short term effects of increased enrolment. In such cases it might be socially desirable to re-allocate cash towards improving reading materials and professional development of teachers. The second is a political economy issue where CCT might be the preferred strategy to avoid the political cost of restructuring the education management system that is dominated by political leaders and unions. In such cases government might opt for a more visible redistribution strategy in terms of CCT even though it leads to weak human capital formation (Reimers et al., 2006). These issues become all the more relevant for the assessment of *KP* in West Bengal as there are reports that the state have shortages of teachers and poor school infrastructure especially at the secondary level (CBGA,2018)[4].

We use the enrollment and learning data from the Annual Status of Education Report (ASER) for the pre and post KP period and employ a triple difference method to identify the program impact on female education. We first compare female enrollment and learning levels in the age cohort 13 to 16 years pre and post KP with that of the boys in the same cohort in West Bengal as they are the control group that has not been exposed to KP. The potential problem of using the treatment and control groups within the same state i.e. West Bengal is that other factors associated with the state policy might affect the girl's education systematically more with respect to that for boys. We reject the parallel trend assumptions and compare changes in school

[4] Over 87,781 teacher posts are vacant in West Bengal, of which 32,661 are under the state and 55,120 are under Sarba Sikhsha Abhiyan.

enrollment and reading and learning outcomes across the neighboring states like Bihar, Odisha and Assam. Here the other states serves as the control group and the girls from the non-policy state serve as the control group. The Difference-in-differences–in differences (DDD) estimates the time change in averages for the female school goers in the treatment state (West Bengal) with that for boys and then nets out similar change in means for the girls with respect to the boys in the control state. It's expected that DDD would thus control for two potentially confounding factors: changes in educational outcomes for the girls across states and changes in educational outcomes for both boys and girls of the same age cohort living the policy change state.

Since one may argue that the schooling outcome for boys may change because of KP due to the potential income and substitution effects within the households, we also employ synthetic control methodology which creates a synthetic control state, which looks similar to West Bengal in terms of the outcome variables before the implementation of KP. Hence one can then argue that any difference in the outcome variable between West Bengal and the synthetic control state post KP is because of the programme and no other confounding factors.

Our results suggest that controlling for household wealth and other amenities as well as village level infrastructure KP has been able to increase female enrollment significantly over the program period. However, we did not find any significant impact in learning outcomes and thus could not establish any connection between school going and educational attainment. We find that the school related infrastructure in the post KP phase for West Bengal is relatively lower compared to other states. Our study shows that KP might have succeeded in terms of delaying the girl's marriage but it has probably not worked when it comes towards increasing empowerment of females. We use DISE data to compare various school infrastructure related variables across West Bengal and all other states.

The findings of the paper are reported in the following schema: the following section (Section 2) analyses the existing work on CCT in education and identifies the contribution of this paper. We discuss the data and estimation strategy in (Sec 3) and the results are reported in Section 4. We offer our final concluding observations in Section 5.

2. CCT and Educational Outcome : Existing Evidence

It has been argued in the literature that households often underinvest in the human capital of the offspring and a redistributive policy like CCT might correct for that[5]. Parents could make suboptimal decisions regarding children's education if there is incomplete information regarding the returns to education particularly for a female child (Fiszbein & Schady, 2009). The "cash" part of CCT introduces an income effect to overcome the credit constraint and the conditionality brings in substitution effect by lowering the opportunity cost of schooling (Baird et al., 2013). Studies have analysed three primary impacts of CCT: enrolment, attendance and learning outcomes. For instance, using 94 studies from 47 CCT programs, Garcia and Saavedra (2017) finds positive enrollment effect in secondary education as well as attendance in schools. In fact, there are evidences that impacts on school enrollment are often largest for children of asset poor households (Filmer & Schady, 2008). However, the evidence regarding learning outcomes is more limited and mixed. No significant impacts are obtained on learning outcomes in terms of test scores in reading and mathematics were obtained by Behrman, Sengupta and Todd (200) in Mexico and similar results were obtained for the CCT in Ecuador by Ponce and Bedi(2008)[6].

[5] Galor and Zeira (1993) for instance is one of the most important work that establishes the linkage between redistributive policies and increase in aggregate efficiency via reduced inequality.

[6] However, if cash transfers initiate enrolment in child that are poorer than those already enrolled in school then there might be a selection issue in the sample. Even within the poor sample, if there are selection on expected returns to schooling those poor children already enrolled in school will have higher average return to schooling than

In India, besides West Bengal CCT related to female education is operational in the states of Assam, Jharkhand, Karnataka, Tamilnadu and Bihar. However, the literatures on the evaluation of these schemes are very scant. A descriptive review of 15 girl child related program is discussed in Sekher (2012) but they did not attempt to identify the impact. We found Dutta and Sen (2018) as the only other study that dealt with impact assessment of KP. They found a heterogenous effect on dropouts and general reduction in age of marriage. However, their study is based on a sample of over 1000 households across six districts in West Bengal and they did not use over time data for comparison. Our study attempts to fill this gap by using a more representative sample and difference and difference measures along with synthetic controls to assess the impact of Kanyashree on educational outcomes.

3. Data, estimation strategy and variables

3.1 Data

We use pooled household data from the Annual Status of Education Report (ASER) from 2011 to 2018, a yearly survey conducted to document the status of education among children in almost all the rural districts of India. The goal of the survey is to get an assessment of the state of education among children in India. Each year's survey covers a random sample of 20–30 households every village and the survey is conducted in around 20 villages in about 550 rural districts of India. In each surveyed household, all children in the age group 3 to 16 are surveyed and learning outcomes of children in the age group 5 to 16 are tested.[7]

3.2 Estimation strategy

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their newly enrolled counterpart. In such cases a comparison of test scores among CCT and non-CCT child may not be appropriate.

[7] More information on ASER can be obtained from http://www.asercentre.org/ (accessed on September 15, 2019)

The timeline of the survey allows us to look at the conditions before and after the implementation of the KP and compare the same with that for the other states as well. To start off, we consider girls of age group 13 to 16 years as the treated group and boys of similar age as the control group. As used in Jayachandran and Lleras-Muney (2009) and Muralidharan and Prakash (2017), boys can serve as an useful control group for the KP because they would have been exposed to all the other interventions that were taking place in West Bengal after the implementation of KP except the benefits of the program. This includes gains in schooling due to increasing household incomes or increased public investment in education along with the gains because of other educational awareness programs.

Accordingly we make use of the difference-in-difference methodology first to get an estimate of the impact of the programme in increasing female enrollment of age group 13 to 16 years. We use the same methodology for estimating the impact on learning outcomes as well. The following regression is estimated only for West Bengal:

(1) $$Y_{idt} = \beta_0 + \beta_1.Female + \beta_2.post + \beta_3.(Female * post) + \beta_4.C_i + \delta_d + (\delta_d * post) + \varepsilon_{idt}$$

Here Y_{idt} is the outcome variable (enrollment and learning outcomes in reading and mathematics) for individual, *i* from district, *d* and time, *t*. The $post$ dummy takes the value of 1 if the year is 2014, 2016 and 2018 and 0 if the year is before 2014. β_3 is the causal estimate of the impact of KP on the outcome variables. The confounding individual, household and village level characteristics which can affect the outcome variables are controlled by C_i. We also control for district fixed effects and the secular district level changes over time to control for any idiosyncratic district level shocks at any point of time that could have affected schooling outcomes.

However it is possible that the trends for the boys after the implementation of the program may not have been parallel to that for girls without the program. In other words, the parallel trend assumption may not hold. This may be because of changing labour market conditions which may systematically affect educational outcomes for boys differently than that for girls. Notably the pre-intervention data from 2014 indicates that 47% of the boys in the age group 13 to 16 years are enrolled in schools whereas for girls the figure is close to 63%. Hence to start off, because of lower enrollment rate for boys, the trend over the next few years might have been different to that for girls, who start off from a better off position in terms of enrollment in West Bengal. To test the parallel trend assumption, we take data from 2011 to 2013, where we run the following regression:

$$(2) \qquad Y_{idt} = \beta_0 + \beta_1.Female + \beta_2.time + \beta_3.(Female * time) + \beta_4.C_i + \delta_d + (\delta_d * time) + \varepsilon_{idt}$$

Essentially, the symbols remain same as that in equation 1. The $year$ variable indicates dummies for the years, 2012 and 2013 with 2011 as the reference.

Largely we were not able to reject the null hypothesis of parallel trends at 5% level of significance. Yet at 10% level, we were able to reject the null. Hence we make use of Triple Difference (DDD) regression to estimate the impact of the KP by comparing the DID estimates from West Bengal and that from a bunch of other neighboring states including Assam, Bihar, Orissa and Jharkhand. We take these states as a comparison group to West Bengal since there are substantial similarities in terms of social, cultural and economic conditions between the states.

We test for parallel trends in the triple difference regression in the period 2011 to 2013. The findings indicate we are unable to reject the null hypothesis of parallel trends since the coefficient on the triple interaction term is found not to be significantly different from zero at 10% level.

The triple difference regression is given as follows:

$$
\begin{aligned}
(3)\quad & Y_{idt} = \beta_0 + \beta_1.Female + \beta_2.post + \beta_4.WestBengal + \beta_5.(Female * post) + \\
& \beta_6.(WestBengal * post) + \beta_7.(Female * post) + \beta_8.(WestBengal * Female * post) + \\
& \beta_9.C_i + \delta_s + \delta_d + (\delta_d * post) + (\delta_s * post) + \varepsilon_{idt}
\end{aligned}
$$

Here, β_8 would give us the unbiased causal estimate of the impact.

The problem with our DDD estimations is that we run regressions for four different states and one may argue that the choice of the control state is arbitrary and ad hoc. It may also happen that because of the KP program targeted to the females, behavior of boys may change. Due to the increased income, an income effect may lead to substitution of labour to schooling. Or it may also happen that due to increased schooling cost of the females, the boys may substitute schooling for paid work (Khandkar et al. 2003). We check this by running a DID regression comparing boys of age group 13-16 years across West Bengal and separately for Assam, Bihar, Orissa and Jharkhand. In none of the regression did we find the enrollment for boys getting significantly changed after the implementation of KP. The findings hold true if we consider only enrollment in grade 8 and above.

Yet, to be sure that our estimates are unbiased and avoid arbitrary choice of control states, we make use synthetic control method (SCM) that has been used in a series of papers (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2015; Peri and Yesenov, 2019). These papers argue that SCM is methodologically superior than the classic DID to address this type of evaluation which depends on arbitrary choice of control groups. In SCM, a linear combination of states forms a better control group for West Bengal than a single state. More specifically, instead of arbitrarily choosing a single state as the control group, we create a synthetic optimal control group that minimizes the pre KP difference with West Bengal for a given set of relevant characteristics that determine educational outcomes. The synthetic state reduces the ad hoc nature of the choice of the control states which were otherwise chosen with applying the SCM methodology. For this, we make use of the ASER database from 2008 till 2018. We calculate the state level year wise estimates of dropout rates, enrollment and learning outcomes among females in age cohort 13 to 16 years.

We consider $J+1$ states indexed by $j=0,1,2,...,J$ and denote West Bengal as 0. The rest of states are referred as the “donor pool” as in Peri and Yesenov (2019). This is the group of 29 large states in India for which data are consistently available for the relevant time period. We now define a vector, M_0 of dimension $k\times 1$ whose elements are equal to the values of variables that can predict the enrollment rates in West Bengal between 2008 to 2013. Similarly, we define a $k\times J$ matrix, M_J, in which row j is the set of values of the same variables and years relative to state, j in the “donor pool.”

The SCM then identifies the vector of nonnegative weights $W^*=(w_1,w_2,...,w_J)$ through which it comes up with a convex combination of variables in states in the donor pool, M_J, to minimize the difference between M_0 and $M_J W$. The expression is as follows:

$$W^*=\arg\min(M_o-M_J W)^{'}V(M_o-M_J W) \text{ subject to } \sum_{j=1}^{J} w_j=1,\ \ w_j\geq 0$$

Once the W^* is identified, we can calculate the outcome variables after the implementation of the KP for the synthetic state, which acts as the control state and compare with that of West Bengal. Here V is a diagonal, positive-definite $k\times k$ matrix that determines the weight for each element of the vector in the objective function. While estimating, we use STATA’s default option for the matrix V, which is chosen to minimize the average squared prediction error of the outcome variable during the pre-intervention period among all diagonal and positive definite matrices (Peri and Yesenov, 2019).

Variables

We look at the impact on two broad indicators of schooling: enrollment and learning outcomes. Within learning outcomes, we look at reading and mathematics scores. More specifically, reading and mathematical ability is coded into dichotomous variables respectively: child level ability to read a story and ability to do division. Enrollment is also coded as a binary variable: whether the child is enrolled in school or not.

Apart from the main variables, we control for independent variables in the regressions that may affect enrollment and learning outcomes. Economic characteristics have been controlled through a number of indicators: whether the house is cemented or not; whether the household has electricity or not and possession of toilet and television and usage of computers. Child level characteristics include his/her age and if he/she opts for private coaching. A number of village level factors have also been controlled for: whether the village has a private school; internet café; private health clinic; bank and cemented road. Controlling for these characteristics would enable us to get a close unbiased estimate of the impact. Notably, robust standard errors are used in the regressions.

4. Results

The results from the DID regression as indicated in equation 1 is shown in Table 1 and table 2. We look at the impact on two broad indicators of schooling: enrollment and learning outcomes. Within learning outcomes, we look at reading and mathematics scores. More specifically as indicated earlier, boys in the age group 13 to 16 years within West Bengal form the control group whereas girls between 13 to 16 years form the treatment group. The findings indicate enrollment for females have grown significantly (1% level) because of the KP. However in terms of learning outcomes, we do observe a significant change indicating KP has been able to enroll the female children to schools, however the program has not been able to improve learning abilities among the female children. We repeat the same exercise taking children between 12 to 16 years of age to estimate the probability of them being enrolled in grade 8th or above with respect to not being enrolled. The findings reveal similar inferences though the effect size of the increase in probability of being enrolled has increased.

Table 1: Impact on enrollment

	Enrollment		Enrollment in government schools	
	(1)	(2)	(3)	(4)
Female*time	0.293***	0.291***	0.179***	0.181***
	(0.087)	(0.087)	(0.059)	(0.059)
Time dummy	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes
Village controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
District*year	Yes	Yes	Yes	Yes
Observations	18535	18535	18,767	18,767
Pseudo R^2	0.276	0.277	0.142	0.144

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

Table 2: Impact on learning outcomes

	Ability to read a story		Ability to do division	
	All	Group 2	All	Group 2
	(1)	(2)	(3)	(4)

Female*time	0.043	0.053	-0.014	-0.014
	(0.346)	(0.047)	(0.043)	(0.045)
Time dummy	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District*year	Yes	Yes	Yes	Yes
Observations	15,608	14,907	15,554	14,855
Pseudo R^2	0.132	0.134	0.146	0.143

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

A strong assumption in the above exercise is that the trend of the outcome variable between boys and girls after the implementation of KP without the program would have been same as that before the program. This parallel trend assumption may not always hold because of a variety of reasons indicated earlier. We test this by running regressions using equation 2 for the period before implementation of KP and examine if the parallel trend assumption hold in this time period. The results are presented in table 3. The estimates suggest no evidence to reject the null of parallel trend assumption as we find the co-efficient associated with the interaction of female dummy and year dummies is indistinguishable from zero even at 10% level.

Table 3: Testing parallel trend assumption (time period: 2011 to 2013)

	Enrollment	Ability to read a story	Ability to do division
Female*time	0.097	0.038	-0.090**
	(0.071)	(0.039)	(0.036)
time (0, 1, 2)	Yes	Yes	Yes

Female dummy	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
District*time	Yes	Yes	Yes
Observations	9,320	7,953	7,916
Pseudo R^2	0.173	0.107	0.121

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time here is a continuous variable (0,1,2 for 2011, 2012 and 2013 respectively.*
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

Yet to be sure of this, we use DDD regression as indicated in equation 3. We separately take four states: Assam, Bihar, Orissa and Jharkhand and estimate the difference of the DD estimates of West Bengal with these states. Here as well we test for parallel trends, which can be gauged by examine the coefficient of the triple interaction of year dummy, West Bengal dummy and the dummy variable indicating that the child is female. We run this regression only for years before the implementation of KP. Except for Assam, in all the other states, the coefficient is found to be statistically insignificant (Table 4). This indicates that the difference between male and female children in West Bengal is not statistically different than that in the other states. This gives us the confidence that post 2014 (after implementation of KP), the difference would have been same had KP not been implemented. Hence, the difference, if any would be because of the implementation of KP.

Table 4: Parallel trends assumption test for DDD (Enrollment)

	Assam	Bihar	Orissa	Jharkhand

Female*time*WB	0.221***	0.048	0.058	0.018
	(0.085)	(0.081)	(0.084)	(0.083)
WB dummy	Yes	Yes	Yes	Yes
time (0, 1, 2)	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes
WB*time	Yes	Yes	Yes	Yes
WB*female	Yes	Yes	Yes	Yes
Female*time	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District*time	Yes	Yes	Yes	Yes
Observations	20,744	39,556	24,912	23,658
Pseudo R^2	0.130	0.222	0.139	0.134

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time here is a continuous variable (0,1,2 for 2011, 2012 and 2013 respectively.*

** 10% level of significance*

*** 5% level of significance*

**** 1% level of significance*

Table 5 shows the results from the main DDD regression outlined in equation 3. Since the parallel trend assumption did not hold for Bihar, we left out the state and ran the regressions only for Assam, Orissa and Jharkhand. The findings reveal a significant increase in female enrollment with respect to that of the boys in comparison to these three states. Interestingly, we did not find large difference in the effect size while considering the three states separately indicating our estimates to be pretty robust. Further, the effect size also is close to what we obtained through the DD estimate. However as we found earlier, no significant effect on learning outcomes was found. The coefficient of the triple interaction is found to be statistically indistinguishable from zero for both, the math and the reading outcomes (Table 6).

Table 5: Impact on enrollment

	All children (13 to 16 years)			Enrolled in govt. school an unenrolled		
	Bihar	Orissa	Jharkhand	Bihar	Orissa	Jharkhand
Time*female*WB	0.322***	0.392***	0.254***	0.109*	0.159**	0.174***
	(0.095)	(0.099)	(0.096)	(0.064)	(0.070)	(0.066)
WB dummy	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes	Yes	Yes
WB*time	Yes	Yes	Yes	Yes	Yes	Yes
WB*female	Yes	Yes	Yes	Yes	Yes	Yes
Female*time	Yes	Yes	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
District*time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,850	45,920	49,653	84,421	46,692	49,653
Pseudo R^2	0.251	0.164	0.167	0.117	0.081	0.134

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

Table 6: Impact on learning outcomes

	Reading a story			Performing division		
	Bihar	Orissa	Jharkhand	Bihar	Orissa	Jharkhand
Time*female*WB	0.023	0.059	0.010	0.013	0.057	0.071
	(0.053)	(0.060)	(0.058)	(0.049)	(0.056)	(0.054)
WB dummy	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes	Yes	Yes
WB*time	Yes	Yes	Yes	Yes	Yes	Yes

WB*female	Yes	Yes	Yes	Yes	Yes	Yes
Female*time	Yes	Yes	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
District*time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,000	38,478	39,833	67,867	38,376	39,739
Pseudo R^2	0.1	0.1	0.1	0.120	0.113	0.109

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*

** 10% level of significance*

*** 5% level of significance*

**** 1% level of significance*

One may argue that because of the KP, enrollment for boys may alter post its implementation because of several factors including increased income or substitution of their schooling with higher schooling for girls. In this case, boys from West Bengal would then not act as a perfect control group. We test this to examine if the trends of enrollment and learning outcomes for boys in the age cohort 13 to 16 years altered after the implementation of the programme. For this, we pool all the male children (13 to 16 years) and run DD regressions to examine if there is a significant shift from 2014 in enrollment and learning outcomes after the implementation of KP for boys in West Bengal with respect to other states, controlling for household, child and district level characteristics. Table 7 presents the results. When compared to Bihar, we find that KP had an impact on boys enrollment but for Orissa or Jharkhand, we find no significant impact.

Table 7: Trends for boys after KP (Enrollment)

	Bihar	Orissa	Jharkhand
Time*boys	0.595**	-0.111	-0.153
	(0.261)	(0.708)	(0.303)
Time dummy	Yes	Yes	Yes
Boys dummy	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	41,178	21,673	24,152
Pseudo R^2	0.282	0.186	0.197

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*

** 10% level of significance*

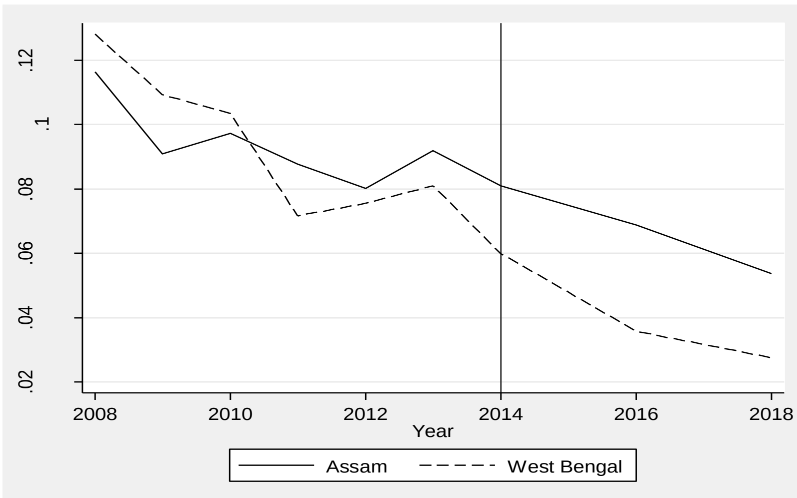
*** 5% level of significance*

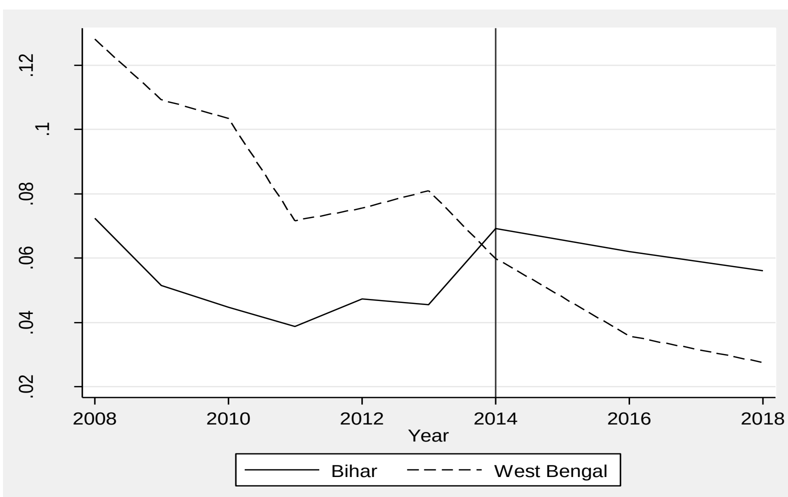
**** 1% level of significance*

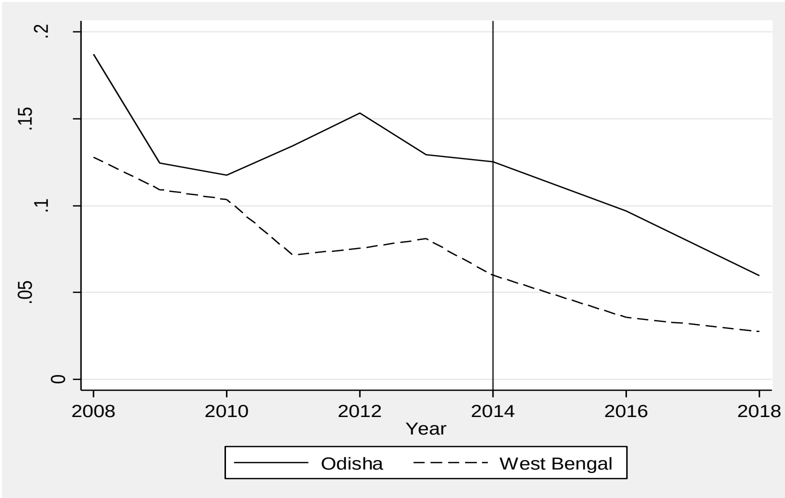
This leaves with two possibilities. Firstly schooling outcomes for boys may have been altered because of KP, due to which they may not serve as the best control. Secondly, as discussed earlier, the choice of control states remains arbitrary and hence we may not get a perfect match for West Bengal without the KP. To address this concern, we make use of synthetic control technique.

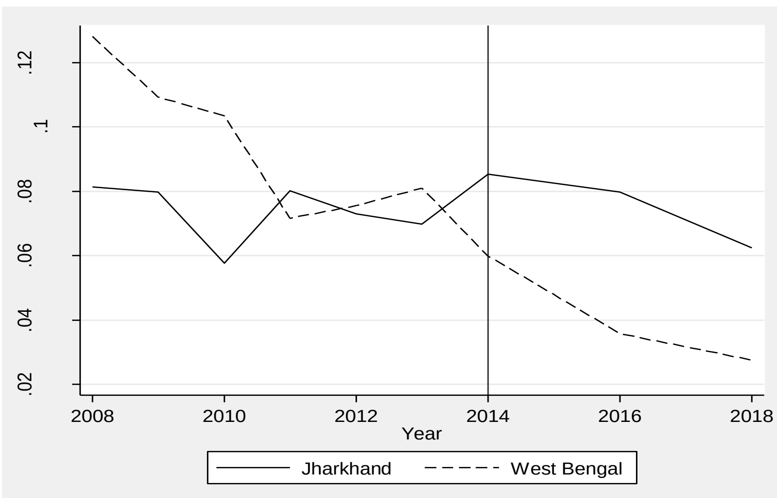
As discussed earlier, synthetic control methodology allows us not to keep the control state as arbitrary but use the data to calculate state level weights such that the synthetic state represents a clone of West Bengal before the implementation of KP. Comparing the dropout trends of West Bengal with Assam, Bihar, Odisha and Jharkhand shows no similarity before the implementation of KP. Figure 1 to 4 compares the trends in female dropout rates (from 2008 to 2018) of West Bengal with the four states respectively. As one can observe, there is little similarity in the trends of dropout rates before the implementation of KP. Hence it cannot be said that any change in the dropout post the implementation may have happened solely due to the KP.

Figure 1-4: Comparing female dropout rates of West Bengal with Assam, Bihar, Odisha and Jharkhand









Hence, we are not basically sure of the state which may act as a good enough control for West Bengal pre-implementation of KP. It is here that synthetic control methods become important as we can now create a synthetic state such that the trends pre-implementation of KP is similar to that for West Bengal. The assumption here is post KP, the trends in the outcome variable in the West Bengal would have been same as that of the synthetic state without the implementation of KP. The difference between West Bengal and the synthetic control state in the outcome variable gives as an estimate of the impact.

The synthetic control method thus produces a figure with two time series plots, one for the treated unit (West Bengal in our case) and one which represents the synthetic control. Unlike what was found through figure 1 to 4, we find the trends of female dropout rate (age 13 to 16 years) for the synthetic control is similar to that for West Bengal (Figure 5). Post 2013, we observe a difference between the synthetic control state and West Bengal. This difference is close to 5% in 2016 and 4% in 2018 and can be seen as the impact of KP. Figure 6 presents the trends for female enrollment rates (age: 13 to 16 years) where we find a slight increase in the outcome variable. This goes in line with our findings from the regression exercise. Notably, the predictors used in predicting the dropout rates for the synthetic control are state wise proportion of mothers who have gone to school at some point of time and proportion of households which are fully cemented along with proportion of households with television and electricity. The outcome variables for 2009, 2011 and 2013 are also used as predictors.

Figure 5: Female dropout rates for West Bengal and the synthetic control

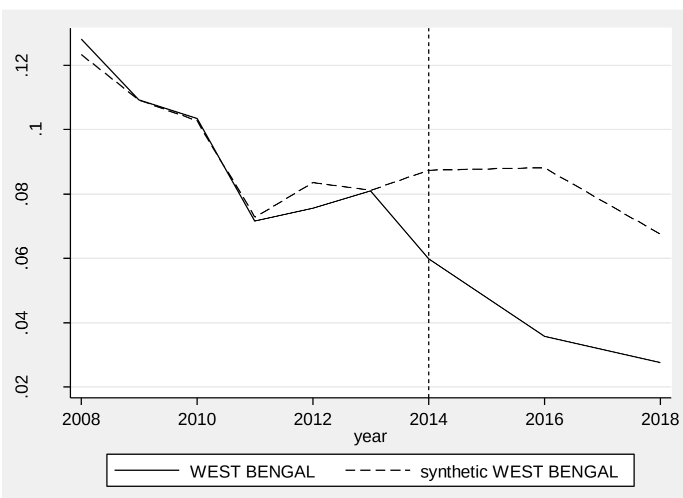
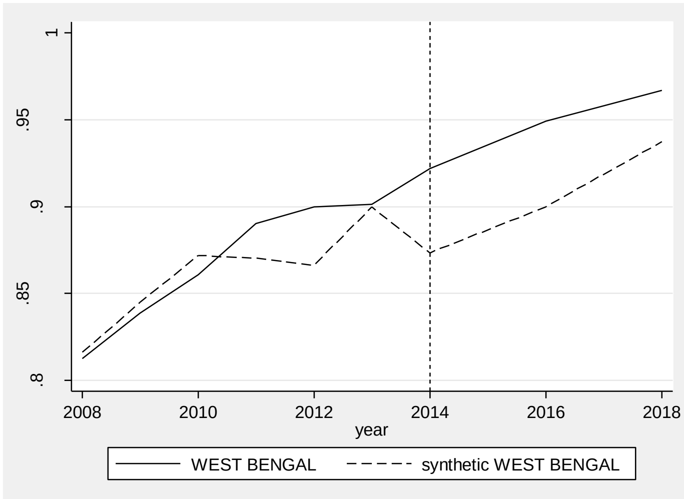


Figure 6: Female enrollment rate for West Bengal and the synthetic state



We also examine the effect on learning outcomes by using synthetic control method. We use the same set of predictors to generate similar figure for reading and mathematical ability outcomes as defined earlier. Figure 7 and 8 presents the trends for the proportion of females in the age cohort 13 to 16 years who can read a simple story and those can perform a simple division respectively. As one can observe, we find no substantial effect on learning outcomes post the implementation of KP in West Bengal though there has been a marked decline in dropout rates for the females. In fact we find a slight drop in learning outcomes in West Bengal compared to the synthetic state after 2013.

Figure 7: Ability to read a story for West Bengal and the synthetic control

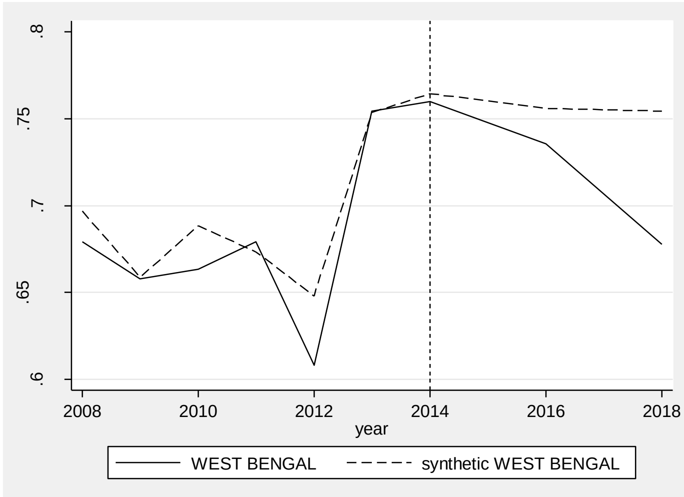
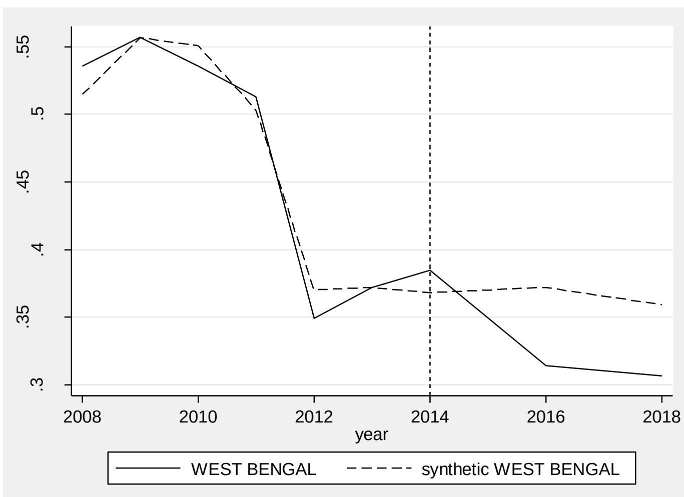


Figure 8: Ability to perform division for West Bengal and the synthetic control



4.1 Robustness checks

We carry out a number of robustness checks. Firstly we check if the KP had an impact on reduction in dropout rates for females in the age cohort 13 to 16 years. Table 8 presents the results from DDD regressions comparing West Bengal separately with Assam, Bihar, Orissa and Jharkhand. As one would expect, we find a significant dip in dropout for females because of the KP when compared across the four neighbouring states of Assam, Bihar, Orissa and Jharkhand.

Table 8: Impact on probability of dropout

	Assam	Bihar	Orissa	Jharkhand
Time*female*WB	-0.373***	-0.374***	-0.382***	-0.321***
	(0.124)	(0.114)	(0.119)	(0.117)
WB dummy	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes	Yes
WB*time	Yes	Yes	Yes	Yes
WB*female	Yes	Yes	Yes	Yes
Female*time	Yes	Yes	Yes	Yes
Household and child level controls	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District*time	Yes	Yes	Yes	Yes
Observations	44,214	83,682	44,956	49,485
Pseudo R^2	0.200	0.267	0.212	0.212

Note. *Estimates from probit regression are presented with robust standard errors given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers, household size, age of the child and his/her age. Village level controls include whether there is a private school, internet café, health clinic, bank and cemented road. Time dummy is 1 for 2014 and thereafter (KP implementation).*
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

District level estimates

The ASER data doesn't follow the individuals so we created a pseudo-district panel by averaging all the household level variables for enrollment and reading scores at the level of the districts (French & Kingdon, 2010). We estimate the following equation

$$Y_{dt} = \beta_0 + \beta_1 post + \beta_2 West\ Bengal + \beta_3 West\ Bengal \times post + \beta_4 District\ Controls + \varepsilon_i$$

Here Y_{idt} denotes the household level enrollment and learning outcomes aggregated at the district level for time *t* and the explanatory variables have their usual meanings. Note that, as we consider the average female educational outcomes at the district level the estimates reported in

Table 9 are difference in difference. Hence, they account only for state specific effect of KP on female enrollment and learning outcomes.

Table 9: District Level Impacts on Enrollment and Learning

	Enrollment	Ability to read a story	Ability to do division
WB*time	0.093**	-.065	-0.147**
	(0.012)	(0.055)	(0.068)
WB dummy	Yes	Yes	Yes
time dummy	Yes	Yes	Yes
District controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	2,534	2,534	2,534
Pseudo R^2	0.44	0.54	0.28

Robust standard errors are given in parenthesis. Household level controls include whether the house is cemented or not, whether the household has electricity connection, toilet, television and uses computers. Time dummy is 1 for 2014 and thereafter (KP implementation).
** 10% level of significance*
*** 5% level of significance*
**** 1% level of significance*

5. Discussion

Our analysis of the impact of KP shows that enrollment of girls in secondary education have unambiguously increased in the post KP period. In fact, the magnitude of the impact of KP is increasing over time. However, we do not have any such impact on learning outcomes. In fact, for both the reading and the mathematical skills we find that KP didn't have any significant effect in augmenting the skills.

Our findings regarding insignificant impact of KP on learning outcomes is in tune with studies like Akresh et.al (2013) who did not find any significant impact of CCT in Nairobi. Moreover, Baez and Camacho (2011) did find Colombia's Familia's en Accion CCT to impact Spanish reading abilities negatively with little or no significant impact on math's score. Similar results have in reported for CCT in China (Mo et al., 2013) and Morocco (Benhassine et al.,2013). In general, evidence regarding impact of CCT on learning outcomes is mixed (Bastagli et al., 2019). We speculate that the insignificant impact on learning outcomes might have arisen due to structural factors like school facilities or household cultural practices regarding female education. For instance, if schools are inadequately staffed then augmenting human capital through increased enrollment might not increase the learning outcomes. To account for this phenomenon we consider the following indicators like Student-Class room ratio (Figure 9), Pupil-Teacher ratio (Figure 10) and Percentage of schools having teachers with no-professional qualifications (Figure 11) for government schools in rural areas from the DISE data.

Figure 9: SCR West Bengal vs India

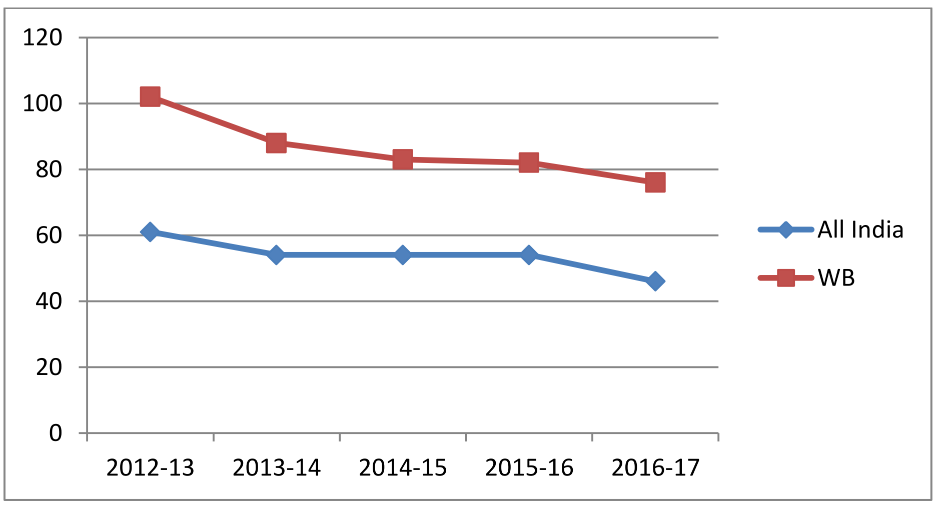


Figure 10: Pupil Teacher Ratio at the Secondary Level –West Bengal vs India

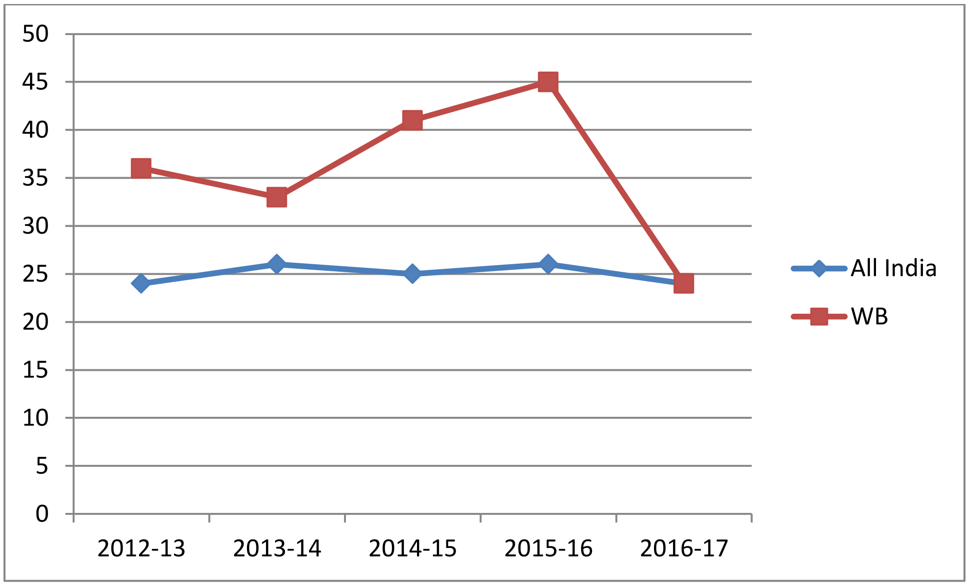
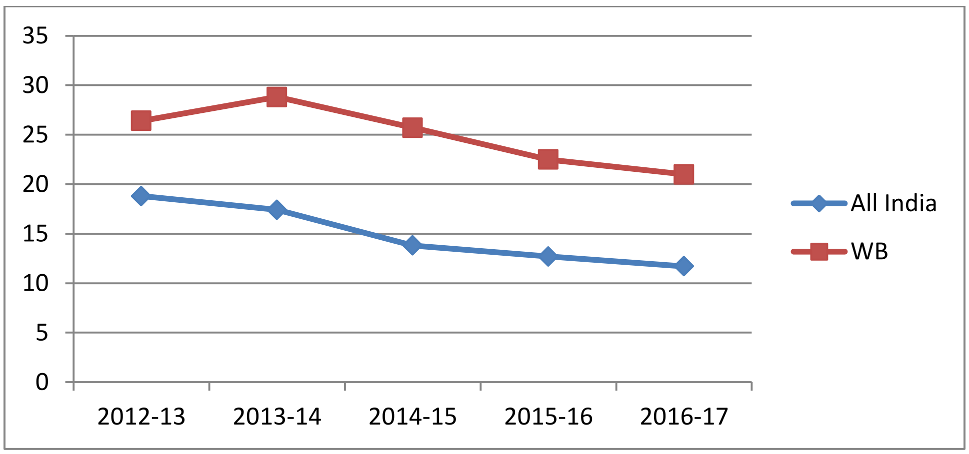


Figure 11: Percentage of Teachers with no Professional Qualification: West Bengal vs India



The SCR as well as PTR is supposed to indicate the adequacy of learning infrastructure and the professional qualification of the teachers would account for the quality of education imparted. As is evident from the figures though West Bengal have PTR figures similar to All India level there are substantial variation in SCR and Professional qualification of the teachers post KP relative to the country average. This leaves open the possibility that though the number of teachers might have kept pace with enrollment there's lack of professionally trained teachers relative to the All India level. However, the extent to which such insufficiencies can be linked to poor learning outcomes among females post KP needs further investigation.

6. Conclusion

Prevalence of child among females has been high in the state of West Bengal. To arrest this, a CCT named KP was implemented in the state since 2013 which targets adolescent girls of 13-18 years of age and offers yearly scholarships on enrollment in government schools. The programme also gives a lump sum grant conditional on the fact that the female continued her education and remained unmarried till 18 year of age. Using pooled individual data from 2011 till 2018, this paper assesses the impact of the KP on female educational outcomes including school enrollment and learning outcomes. Standard impact evaluation techniques including double difference, triple difference and synthetic control methodology have been applied to obtain unbiased estimates of the impact.

Our findings suggest a robust and significant impact of the programme on increasing adolescent female enrollment and hence curbing their school dropout as well. However the learning outcomes are found to be less likely to be affected by the programme. The findings remain consistent across specification, methodology and control groups that are selected. We further use DISE data to study school infrastructure in West Bengal and compare that with India across some of the previous years. The findings reveal though there has been an improvement, the gap in adequate infrastructure between West Bengal and that in India remains substantial. This indicates that though there has been a substantial increase in enrollment after the implementation of KP, the school infrastructures have not improved adequately. This possibly explains the insignificant impact of the programme in improving learning outcomes. Beside structural factors household culture might also influence decision making regarding female education. If households attach a higher weight to girl child doing household chores then they would allow the girls to substitute household labour by school hours as long as *KP* grants compensates for the missing hours. The allocation would be governed by the extent of patriarchy in the household and if the elasticity of substitution between school and household chores are inelastic then the girl child might have to allocate the same labour hours irrespective of her school hours. However, this would require detailed analysis of time use data in the pre and post KP period and we relegate this as an interesting possibility of future research.

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