The Impact of a Conditional Cash Transfer Program on Household's Fertility Choices in India

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Abstract. This paper tests the impact of a conditional cash transfer program called the Janani Suraksha Yojna (JSY) launched by the Government of India in 2005 to reduce maternal and neonatal mortality rates in the country, on fertility decisions made my households with respect to the gender composition of their children. By providing access to prenatal sex determination technology on one hand through a precondition of undertaking at least 3 ante natal check and reducing the cost of childbearing on the other through a cash transfer on a live birth in a health institution, this program unintentionally influenced the sex selective behaviour among Indian parents. This paper uses the recent DHS IV data and employs a triple difference estimator that relies on exogeniety of state of residence of program beneficiaries, timing of the program and exogeniety of sex of the first child to estimate the effect of this program on sex selective abortions in India. The paper finds that contrary to previous work on sex selective abortions, JSY led to an increase in number of girls being born and at the same time an increase in infant mortality among girls. It also provides suggestive evidence of nutritional gender gap among the surviving children in India.

Keywords: Sex-Selective Abortions · Fertility · Gender Gaps · Conditional Cash Transfer Program.

1 Introduction

Households make several decisions regarding their fertility behaviour, like when to start having children, how many children to have, the sex composition of children among others. These decisions are shaped by their preferences and prevailing cultural norms. Particularly in a country where son preferences are widespread, decisions about sex composition of children become important. India is infamous for its preference for sons and discriminatory behaviour towards its daughters. Starting from the seminal work of Amartya Sen in 1990, there has been steady literature documenting the problem of missing girls in India (Klasen [1994], Klasen and Wink [2002],Arnold et al. [2002], Agnihotri et al. [1998]).The Economic Survey of India 2017-18 puts this number at 63 million missing women in India [3].This paper therefore specifically focuses on the fertility decisions household make with respect to the sex composition of their children.

Government of India, in 2005 launched a conditional cash transfer scheme with an objective to reduce maternal and neonatal mortality. This scheme incentivised households to use health services by integrating cash assistance for every live birth in health centers along with prenatal care which included antenatal checkups and postnatal care. This scheme also recruited health workers who facilitated the program in their respective villages by identifying beneficiaries and assisting them with registration, antenatal checkups and postnatal care. By providing access to health facilities on one hand and reducing cost of bearing children on the other hand, this program makes an interesting case to study fertility decision making among Indian households.

Discrimination against girls leading to skewed child sex ratios is a persistent problem in India. India's child sex ratio according to 2011 census was 108.8 boys per 100 girls whereas the average child sex ratio in the developing

[3] http://mofapp.nic.in:8080/economicsurvey/

world was between 103 - 106 boys per 100 girls [4],[5]. Figure 1 shows the evoluion of sex ratio among children between the age of 0-5 from 2005-06 to 2015-16. [6] The natural sex ratio among children should be 106 boys per 100 girls [Bhaskar, 2007]. Any deviation from this sex ratio indicates human interference. As is evident in the figure most of the deterioration in child sex ratio happened in the northern states of India where preference for sons is rampant.

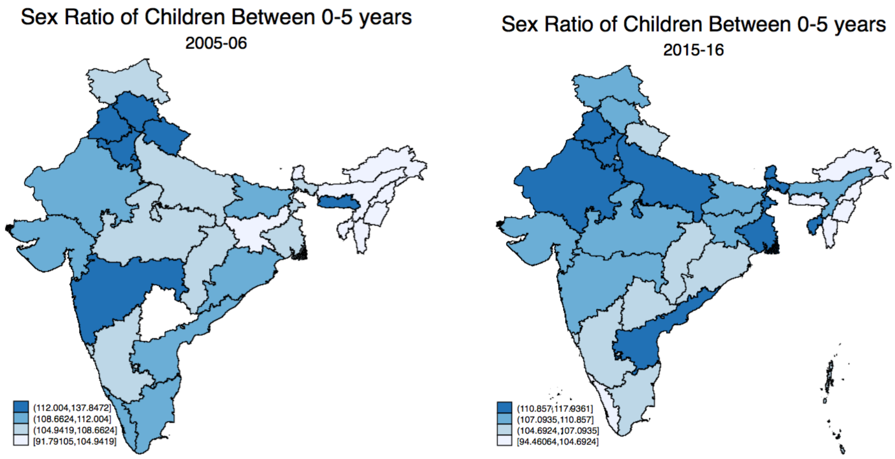


Fig. 1. Sex Ratio of Children Between 0-5. Sex ratio is computed as number of boys born per 100 girls.

Literature has also shown that the problem of skewed sex ratio becomes worse for children born at higher birth orders [Jayachandran and Pande, 2017]. Figure 2 plots sex ratio at birth from 1990 to 2016 at various birth orders. The thick red line is the reference line indicating the natural sex ratio at birth. The dotted light blue line plots sex ratio at birth for children born at birth order 1 i.e. the first born child. This line closely follows the reference line indicating that households seldom sex select at first birth. The dashed red line indicates sex ratios for children born at birth order 2 and as can be seen this line already has started moving away from the reference line. Lastly, the thick green line plots sex ratio for children born at birth order two and above and the distance between this line and the reference line is much more skewed towards males.

[4] http://data.un.org/Data.aspx?d=PopDiv&f=variableID%3A52
[5] http://pib.nic.in/newsite/PrintRelease.aspx?relid=103437
[6] Throughout this paper, sex ratio is computed as number of boys per 100 girls.

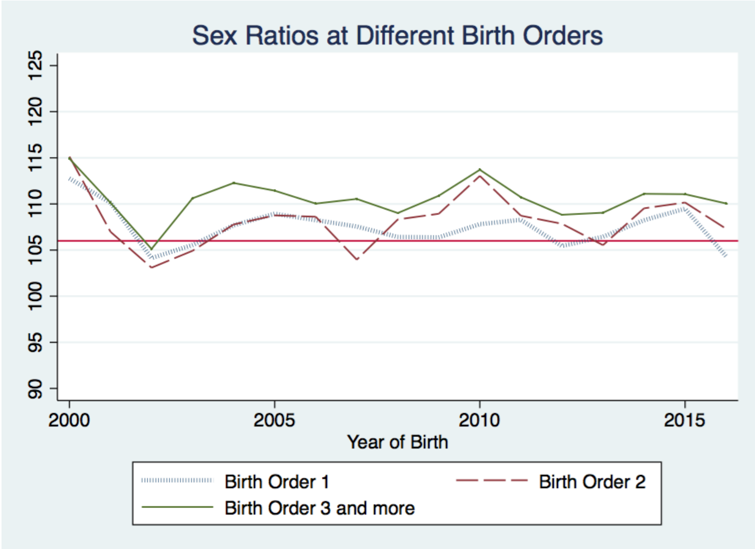


Fig. 2. Sex Ratio of Children by Year. Sex ratio is computed as number of boys born per 100 girls.

Literature has linked various channels that influence the sex selective behaviour among Indian households. These channels range from access to pre natal sex determination technologies like ultrasound [Bhalotra and Cochrane, 2010], price of gold [Bhalotra et al., 2018a], dowry and marriage institution [Borker et al., 2017] and the religious identity of the political leader [Bhalotra et al., 2018b]. The channel that has received most attention in literature is the access to ultrasound technology (Bhalotra and Cochrane [2010], Anukriti et al. [2018]). The JSY program by giving access to ultrasound technology and at the same time by reducing the cost of bearing children could have altered fertility decisions at several levels, particularly at the ability of household to choose the sex of their child.

Household's preference for sons originate from a variety of religious and cultural norms where sons are viewed as a source of socio-economic support and girls are liabilities. In Hinduism, the most dominant religion in India, sons are expected to perform funeral service rituals like lighting the pyre of the deceased parent. Further, sons are also responsible for taking care of their parents in old age, thereby providing a source social security. Even though daughters have a legal authority to an equal share of inheritance of the family wealth, households prefer to keep it within their family by bearing a son instead of giving it away to a daughter who eventually moves to different household after marriage. Lastly, there is some evidence in the literature that labour market outcomes for sons are higher than those for daughters [Rosenblum, 2013]. All of these factors combined result in son preference among Indian households.

These preferences are in turn reflected in the discriminatory behaviour of households that operated through two channels.

– Post-natal discrimination: Under this route, households tend to keep having children until they reach their desired number of sons. This has been termed as target rule/stopping rule based fertility in the literature. Girls born to households following this channel end up in larger families with large number of siblings. As a result they have to compete for limited resources which often leads to their neglect and early death.
– Pre-natal discrimination: Households following this route indulge in sex selective abortions so that that they can have smaller families by aborting the fetus of the child if its a girl [Jayachandran, 2017].

Previous work has shown that prior to advent of pre-natal sex determination technology like ultrasounds in India, post-natal discrimination was the most widely followed channel of gender discrimination by households to achieve their desired sex composition of children, even though it meant that they had larger families. However, since ultrasound became prevalent, households changed their behaviour from post-natal discrimination to pre-natal discrimination (Bhalotra and Cochrane [2010], Jayachandran [2017]).

By exploiting the exogenous timing and geographical location of households eligible for the JSY conditional cash transfer program, our paper shows that the program reduced sex selective behaviour among households eligible for the program. The intention to treat effects show that among households eligible to receive the program the likelihood of having a girl at next birth is 4.8 percent higher than those who were not eligible. The magnitude of this effect increases to 12.4 percent among families with first born child as girl. These are the families that have been shown in literature to have higher incentives to sex select. Further, the paper finds that among the additional girls born, the program increased infant mortality among girls under the age of five compared to boys. Lastly, the paper finds some suggestive evidence that for the girls that survive, their nutritional outcomes are lower than those of boys. Our results suggest that the program caused a reversal in behavioral trend among households from pre-natal discrimination back to post natal discrimination for the households that were eligible to benefit from it.

Our paper is, to the best of our knowledge, the first one to show the trend reversal in discriminatory practices due to the cash transfer program. We show that this reversal happened among households that have been shown in the literature to have higher propensities to sex select i.e. rich upper-caste households and households where first born child is a girl. Rest of the paper flows as follows: Section two gives a brief overview of literature on sex selection in India and the JSY program. Section three describes how JSY program was rolled out in India . Section four briefly describes the dataset used for the analysis. Section five reports the empirical results and section six provides the robustness checks and falsification tests for the results. Section seven provides a discussion with additional evidence on well-being of surviving children and section eight concludes the paper.

2 Literature Review

Literature looking at fertility decisions of households originated with the pioneering work by Becker [1960] where he studied the problem of household's decision making regarding fertility within the framework of consumer theory, to show that changes in family sizes are a result of variations in family incomes and shadow prices/opportunity costs of children. He further argued that households have preferences not just for quantity of children but also for quality per child, an implication that he further develops in Becker and Lewis [1973]. Child quality is generally, captured by the expenditure per child or human capital formation with a view that better investment in children can reap better returns in future.

While several empirical studies confirm the hypothesis that number of children and quality of children are substitutes [Rosenzweig and Wolpin, 1980, Rosenzweig and Schultz, 1985], there exists evidence that households also have preference for sex of their children. Clark [2000] provides early evidence from India on prevalence of son preference and its consequent effect on child sex composition in Indian families. In the absence of access to technologies that can pre-determine the sex of unborn children, households with strong preference for son are likely to follow stopping rule where they continue to have children till they achieve their desired number of boys [Jensen, 2012, Rosenblum, 2013, Anukriti et al., 2018].

An extension to Becker's generic fertility theory was proposed by Ben-Porath and Welch [1976] who argued that parents also care about sex of their children. These preferences for a particular sex (mostly boys in developing country context) may stem from tastes. For instance households may prefer to have balanced sex composition of children. They could also be driven by culture and social norms, for instance, in Hinduism boys are required to light the pyre of their dead parents. Or could just be driven by economic incentives where boys might be expected to engage in market activities and take care of their parents in the old age [Rosenblum et al., 2013].

With the advent of pre-natal sex determination technologies like ultrasound and amniocentesis, households can determine the sex of their children before they are born. This increased the likelihood of households with strong preference for boys to abort their fetus if its a girl [Bhalotra and Cochrane, 2010, Anukriti et al., 2018]. Bhalotra and Cochrane [2010] provide the first estimates of the causal effect of ultrasound technologies on sex ratio at birth in India. While they find increased prevalence of sex selective methods after the launch of ultrasound technology in India, they also find that incentives for sex selection are increasing in birth order and family's socio-economic status. A recent paper by Anukriti et al. [2016] shows that with increased prevalence of sex selection by households, use of stopping rule to get desired number of boys is on decline and there is an increase in early life investments for surviving girls by households in India. While parental preference combined with access to technology can impact the observed child sex ratios, but to interpret the cause of this variation it is important to also understand other factors that may impact child sex ratios. Bhaskar and Gupta [2007] review biological and socio-economic factors that affect child sex ratios. They find that biologically, boys have higher infant/child mortality rates which leads to a higher sex ratio in the early years of childhood. While, economic development leads to improvements in health and nutrition reducing infant mortality and still births. This is associated with fall in sex ratio as it disproportionately benefits the weaker sex (boys).

Empirically, several studies have examined the issue of deteriorating sex ratios in India. One of the early papers reflecting on this problem is by Dyson and Moore [1983] who argue that cultural factors and female autonomy explains the prevailing male bias in North Indian communities. Further research has explored the issue of high female mortality among girls as a result of discrimination amongst them in India. Pioneering work by Sen [1990] was the first to estimate the gender bias in mortality at any age and referred to it as 'missing women'. Subsequent work by others also provides further evidence of existence of this bias in India [Gupta, 1987, Klasen and Wink, 2002, Anderson and Ray, 2010].

Previous research on JSY has studied the impact this scheme has had in improving maternal mortality and neonatal mortality rates in India find mixed effect of the program. Lim et al. [2010] were one of the first to evaluate the impact of JSY. Using three analytical approaches of matching, with-versus-without comparison and difference in difference, they find that JSY had a significant effect on increasing antenatal care, in-facility births and decreasing neonatal deaths in families that received the CCT. A replication of the results from this study, done by Carvalho and Rokicki [2015] confirms these results. Powell-Jackson et al. [2015] using differences in differences estimates that exploit heterogeneity in the implementation of the program across districts find that though the program increased institutional deliveries, it had no significant impact on maternal and child mortality. Joshi and Sivaram [2014] also find that the program had limited impact. While it increased number of medically supervised births, there was no improvement in ante-natal and post-natal care. Carvalho et al. [2014] study the impact of JSY on child immunizations and show that the program significantly increased immunization rates, post-partum checkups and healthy early breastfeeding practices. While Nandi and Laxminarayan [2016] find that the program increased the probability of child birth or pregnancy in states already experiencing high population growth. Preliminary work by Alfano et al. finds that the program suppressed sex ratios at birth in areas characterized by strong preferences for sons.This paper contributes to latter literature in studying the unintended consequences of JSY on child sex ratio in India.

This paper adds to this existing literature by providing additional empirical evidence from nationally representative household survey on sex selective abortions in India. By using the exogenous variation in timing of JSY program and hence access, it estimates the impact program had on influencing household's fertility decisions. Further, all of the above studies use data prior to year 2006. This paper uses most recent household level data with detailed information of women's birth history to estimate this effect and hence provide the most updated evidence.

3 About Janani Suraksha Yojna (JSY)

In 2005, the Government of India launched Janani Suraksha Yojna (JSY), a conditional cash transfer program to with a dual objective of reducing the number of maternal and neonatal deaths nationwide. This scheme promoted safe motherhood by providing cash incentives to women if they delivered their children in either government hospitals or an accredited private health institutions. A further condition, to receive the full cash incentive was that the mother should undertake at least 3 prenatal check ups that include ultrasound and amniocentesis.

Eligibility for receiving the the conditional cash transfers (CCT) was dependent on the place of residence, income level and caste of the household. States (Uttar Pradesh, Uttranchal, Bihar, Jharkhand, Madhya Pradesh, Chhattisgarh, Assam, Rajasthan, Orissa and Jammu & Kashmir) with low rates of institutional deliveries were classified as Low Performing States (LPS) and rest of the states were the classified as High Performing states (HPS). Since institutional delivery rates are highly correlated with maternal mortality and child mortality rates [Joshi and Sivaram, 2014], this program attempts to improve maternal and neonatal mortality through institutional deliveries. In LPS, all pregnant women were eligible and the benefits were paid regardless of whether women delivered in a government hospital or in a private accredited health center. Benefits were provided to these women of the low performing states regardless of the birth order of their children. In HPS, only women who are classified as living below the poverty line (BPL) or belonging to scheduled caste (SC) or scheduled tribe (ST) were eligible for program benefits. The eligibility in HPS was restricted to women who were 19 years of age or older and were giving birth to their first or second child. Women's eligibility for the program as well as the remuneration they received was different across the LPS and the HPS. Women in low- performing states were eligible to receive Rs. 1400 (20$) in rural areas and Rs. 1000(14$) in urban areas, per birth. Women in high-performing states were eligible to receive Rs. 700(10$) in rural areas and Rs. 600 (9$) in urban areas, per delivery.

A novel feature of the program was the introduction of accredited social health activist (ASHA) who acted as a link between the government and the beneficiaries. Adult women who have a 12th grade certificate and are from the same village as the beneficiaries were generally chosen as ASHAs to ensure that the beneficiaries develop trust in these health workers and follow their advise regarding pregnancy. The role of the ASHA is to facilitate the program in the village by identifying pregnant women and registering them into the scheme by providing them with a personalized JSY card wherein each of their pregnancy is recorded. Her duties include assisting the beneficiary to access prenatal health services like getting at least three ANC checkups including TT injection and IFA tablets. The ASHA is also supposed to counsel pregnant women to undertake safe deliveries and escort them to the health centers. Finally she is supposed to provide information to the new mother on the benefits of breastfeeding and immunization of the infant. The role of the ASHA in essence is to ensure that the pregnant women in her village have a safe motherhood experience by encouraging institutional deliveries and administering access to prenatal and post natal health services. To keep the ASHA sustained in the system, she received performance based incentives depending on how many mothers could she motivate to undertake institutional deliveries. ASHA package was Rs 600 for rural areas and Rs 200 for urban areas and was similar across the low and high performing states.Table 1 shows the cash incentives available to pregnant women and Asha workers for every live birth under this program.

Category	Rural area		Total	Urban area		Total
	Mother's package	ASHA's package	(Amount in Rs.)	Mother's package	ASHA's package	(Amount in Rs.)
LPS	1400	600	2000	1000	400	1400
HPS	700	600	1300	600	400	1000

Table 1. Source: http://www.nhm.gov.in/nrhmcomponnets/reproductive-child-health/jsy.html

In June 2011, a few additional features were added to the program to eliminate all out of pocket expenditures related to related to deliveries and treatment of the sick newborn. This included normal deliveries and cesarean operations in Government health institutions in both rural urban areas. While no provisions under the original program were changed, new features like providing drugs, treatment upto 48 hours, transport from home to health institutions and diagnostics for the mother and child at zero costs were added. This late diffusion program, now called the Janani Shishu Suraksha Karyakram (Mother Child Safety Program) further ensured better facilities for women and child health services.

4 Mechanisms

The cash transfer scheme on one hand reduced the cost of child bearing while on the other hand it increased access to prenatal health services which have been shown in the literature to have pervasive effects on fetal sex selection thereby possibly influencing household's fertility decisions with respect to the gender composition of their children. We hypothesize four possible channels through which this program could have altered parental fertility choices.

First, JSY offered households with incentives to undergo atleast three prenatal check-ups like ultrasound scans etc, thereby giving technological access to all households. This could have increased access to PNSD (Pre-Natal Sex determination) technology of households who might previously have been excluded from public health care. Literature has shown that parents with a strong son preference are likely to use this access to choose the preferred sex of the child by aborting the fetus if it's a girl. If this channel is dominant we're are likely to see an increase in sex selective behaviour and a decrease in the likelihood of a girl birth at each birth order. The underlying assumption for this mechanisim to hold is that there are illegal ways that parents can use to perform sex-selective abortions. Second, besides incentivizing households, JSY also offered performance based benefits to the health activists or ASHAs for every institutional delivery of JSY beneficiary in their village. As the ASHA received her benefit along with the mothers after the delivery of the child, she could dissuade the mother from undergoing sex selective abortions thus increasing the likelihood of the successive girl births. Thirdly, one of the duties of the ASHA is to identify the pregnant women eligible for the scheme in her village and register her into the scheme as well as record her pregnancies. This formal registration into the program entails the preparation of a JSY card for the pregnant woman. Revealing the sex of the fetus and conducting sex selective abortions is illegal in India according to the PCPNDT ACT 1994[7](Amended 2003). A formal registration into the system would entail the knowledge of the pregnancy to not only the ASHA but also perhaps to the doctors and nurses at the health centers. This could possibly deter parents to undertake sex selective abortions. Lastly, the program provided cash transfers for deliveries at health centers, consequently reducing the costs involved with childbearing. If this channel dominates, then we expect there to be increase in probability of having girls in our treatment group over time. Thus each of these channels except the first when dominant would increase the likelihood of female births at every birth order.

[7] Pre-Conception and Pre-Natal Diagnostic Techniques (PCPNDT) Act, 1994 is an Act of the Parliament of India enacted to stop female foeticides.The Act provides for the prohibition of sex selection, before or after conception. It regulates the use of pre-natal diagnostic techniques, like ultrasound and amniocentesis by allowing them their use only to detect abnormalities.

5 Data and Descriptive Statistics

The data used in this paper for analysis is the recent wave of DHS-IV that was collected during 2015-2016. DHS collects detailed information on every birth of eligible women (ever married 15-49 years old) in the sample. Using this information we are able to create a panel of ever-born children to a mother over time in each state of India. While the data has birth history from 1980 onwards we restrict our analysis to families with first born children on or after 2000 or in other words families that start their fertility decision on or after the year 2000. While our results are robust for the entire sample, we suspect that a full sample analysis could possibly conflate the effects of an earlier ultrasound shock of 1995 when the local production of these machines began in India. The ultrasound or PNSD technology came to India in 1985 and became widespread from 1995 onwards (Bhalotra and Cochrane [2010]) . The areas to first get access to this technology are likely to be urban areas, therefore including them in the sample will bias our results. This is also the reason to restrict the analysis to rural families.

Our sample for analysis is all families in rural India that started their fertility on or after 2000 and belong to upper caste or other backward castes (OBC) and do not fall below the poverty line. Table 1 records the descriptive statistics for the treatment and control group. We see that most of the characteristics are similar between the two except the proportion across religious groups. The treatment group has a larger proportion of Muslims, 18.7% as opposed to the 10.9% in the control group. This difference is consistent for Christians with 0.3% in the treatment states and 3.4% in the control states. The differences across religious groups are statistically different as reflected by the Figure 3. Here we plot the coefficients of all the covariates for both the groups at a 5% level of significance. As observed in the descriptive statistics table, significant differences appear between both the groups for religion and ownership of resources. Significantly more households in the treatment group own a truck and a cycle while TV, refrigerator and electricity is owned by significantly more households in the control. The self reported ultrasound usage is also significantly more for the household of the control group however the significance is relatively weak.

Fig. 3. Test of non differential treatment and control groups

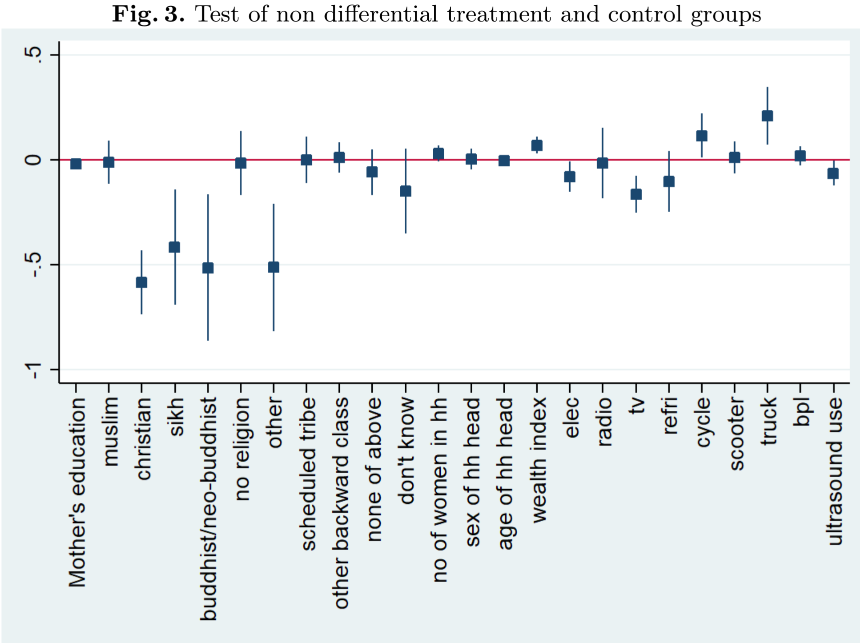


Table 2. Descriptive Statistics

	Treatment Group		Control Group	
	Mean	SD	Mean	SD
Families with first girl	0.482	0.5	0.481	0.5
Mother's years of Schooling	6.008	5.111	8.56	4.531
Hindu	0.8	0.39	0.75	0.43
Muslim	0.187	0.39	0.109	0.312
Christian	0.003	0.054	0.034	0.18
Sikh	0.006	0.078	0.079	0.27
Buddhist	0.001	0.025	0.01	0.1
Jain	0.001	0.03	0.001	0.027
Forward Castes	0.297	0.457	0.44	0.496
No of elig women in the hh	1.527	0.919	1.411	0.769
Sex of the household head	1.115	0.319	1.112	0.315
Age of the household head	44.799	15.141	47.906	15.206
Wealth Index: Poorer	0.148	0.355	0.146	0.353
Wealth Index: Middle	0.179	0.383	0.197	0.398
Wealth Index: Richer	0.228	0.419	0.243	0.429
Wealth Index: Richest	0.325	0.468	0.293	0.455
Electricity	1.157	1.463	1.186	1.143
Radio	0.487	1.604	0.359	1.325
Television	0.887	1.556	1.069	1.205
Refirgerator	0.585	1.601	0.734	1.312
Bycycle	0.94	1.542	0.728	1.313
Motocycle	0.761	1.582	0.784	1.302
Car	0.441	1.602	0.383	1.328
Proportion of girls	0.476	0.5	0.475	0.5
Number of Mothers	52,668		26,820	

6 Empirical Methodology

6.1 Difference-in Difference Estimation

The goal of this paper is to estimate the causal effect of the JSY program on fertility decisions of the households and its consequences on child welfare. Given the way the program was rolled out, we have two comparison groups, one which received the program i.e. upper caste non-poor households in LPS and a similar group that didn't i.e upper caste non-poor households in HPS. To estimate JSY's causal impact on fertility decisions, we use a difference-in difference estimation strategy where we compare our treatment and control groups before the program and after the program. As can be seen in the above figure 3 the two groups are similar on most of the characteristics except at the level of religion and ownership of resources . We therefore, use mother fixed effects in our estimation to control for all mother level confounding factors.

The first estimation that we run is a standard D-I-D estimation that relies on exogenous timing of the program and eligibility of families to access the program based on their residence. For child born at birth order b to mother i in year t and state s, we estimate the below specification:

$$Girl_{bist} = \beta_0 + \beta_1 Treat_i \times Post_{2006-15,t} + \beta_2 Treat_i + \beta_3 Post_{2006-15,t} + StateTime_{st} + \delta_i + \lambda_t + \theta_b + e_{bist} \quad (1)$$

$$\begin{aligned} Girl_{bist} = \beta_0 + \beta_1 Treat_i \times Post_{2006-10,t} + \beta_2 Treat_i \times Post_{2011-15,t} + \beta_4 Treat_i + \beta_5 Post_{2006-10,t} + \\ \beta_6 Post_{2011-15,t} + StateTime_{st} + \delta_i + \lambda_t + \theta_b + e_{bist} \end{aligned} \quad (2)$$

The dependent variable $Girl_{bits}$ is a dummy variable that is 1 if the child born at birth order b is a girl and 0 if its a boy. $Treat_i$ is the treatment variable that is equal to 1 if the mother is from the treatment group or 0 if she is from the control group.$Post_{2006-10,t}$ captures the early diffusion period of the program. It is 1 if the child at birth order b was born between 2006 to 2010 i.e. five years after the program and is 0 if they were born between 2000 to 2005 i.e. five years before the program. Similarly, $Post_{2011-15,t}$ captures the late diffusion period and is equal to 1 if the child at birth order b was born between 2011 to 2015 and is 0 if they were born between 2000 to 2005. $\delta_i, \lambda_t, \theta_b$ are mother fixed effect, time fixed effect and birth order fixed effect respectively, to control for any confounding factors [8]. Lastly, $StateTime_{st}$ captures the state and time trend i.e. anything that changes over time by states gets absorbed in this variable[9].

Table 3 presents the results for D-I-D estimation. The two columns show analysis done by clustering standard errors at the state level as variation in program eligibility varies at state level. In the first column, we compare the period from 2006-2015 to 2000-2005. In the second column the post period of 15 years is divided into a late diffusion periosd and an early diffusion period. The key variables of our interest are (i) $Treat \times \text{Post}_{2006-10}$ that compares differences in probability of having a girl child across treatment and control group five years before the program to the differences across these two groups five years after the program; (ii) $Treat \times \text{Post}_{2006-15}$ that compares differences in probability of having a girl child across treatment and control group five years before the program to the differences across these two groups in the last five years; and (iii) $Treat \times \text{Post}_{2006-15}$ that captures the differences in probability of having a girl child across treatment and control group five years before the program to the differences across these two groups in 10 years after the program. This differentiation is done firstly, to see how the impact changed over two diffusion periods given that new features were added to the policy in 2011. Secondly, we have information of the anthropometric outcomes for children born in late diffusion

[8] All regressions were also run with including state fixed effects as an additional control but that had no impact on the results.

[9] Pischke [2005] suggests introducing state time trends among other regressors to improve the robustness of the D-I-D identification.

period only, so we can neatly, tie the impact the program had on the sex ratio of the cohort to the average welfare impact on children in these cohorts later in the paper.

Table 3: Impact on sex selective abortions

	(1) Girl	(2) Girl
$\text{Treat}\times\text{Post}_{2006-15}$	**0.0481****	
	(0.0205)	
$\text{Treat}\times\text{Post}_{2006-10}$		**0.0405****
		(0.0187)
$\text{Treat}\times\text{Post}_{2011-15}$		**0.0867****
		(0.0337)
StateTime Trend	0.0000	0.0000
	(0.0002)	(0.0002)
Mother FE	Yes	Yes
Time FE	Yes	Yes
Birth Order FE	Yes	Yes
N	144872	144872
R^2	0.3528	0.3529
Mean	0.47	0.47
p-value for equality of coefficients		0.01

Standard errors in parentheses clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As can be seen in table 3 the difference-in-difference estimates are positive and significant in both early diffusion phase and late diffusion phase. As expected, magnitude is higher in late diffusion phase. So in comparison to children born before the program started, mothers eligible for the program are 8.6 percent more likely to have next child as a girl than their counterparts in control groups. This result is interesting as it shows reduction in sex selective behaviour among the groups that have been known in literature to sex select i.e. the rich upper caste society in India [Borker et al., 2017]. Note here that we are comparing the child gender outcomes for mother's who had atleast one birth before and atleast one birth after the program. Women who complete their fertility before the program and women who begin their fertility after the program are dropped from out analysis. Thus we look only at the transitional mothers.

6.2 Triple Difference Estimation

One drawback of the D-I-D specification is that the treatment and control groups differ in socio-economic variables, a key assumption for causality of DID results. A more robust estimate of the program in this situation can therefore be obtained by using an additional treatment and comparison groups within the treatment group [Wooldridge, 2007].This robust estimate can be achieved through a triple difference estimator that will provide a causal estimate of the effect of JSY on sex selective abortions. A key advantage of this estimator is that it allows to non-parametrically control for large number of confounding factors [Anukriti et al., 2018]. We use sex of the first child as an additional source of variation for our triple difference estimator (D-D-D).

Sex of the first child has been shown to be random in literature as parents do not sex select in their first birth (Rosenblum et al. [2013]; Bhalotra and Cochrane [2010]; Arnold et al. [2002] and Gupta [1987]). It is also well established that families that are randomly assigned girls as the first child by nature are more likely to sex select at next or higher birth orders than families that got the first child as a boy (Rosenblum et al. [2013]; Bhalotra and Cochrane [2010]; Arnold et al. [2002]). This is also evident from figure 1 where the sex ratio becomes highly skewed at birth orders 3 or more. Therefore, by taking additional difference in proportion of girls born at birth order 2 or more between families with first born girls and families with first born boys in treatment and control groups over time, we will be able to difference out any confounding factors that may cause systematic difference in treatment and control groups as well a changes in treatment or control groups over time that we were unable to control for in previous specification. This would control for any other state specific programs that could have changed over time and could have possibly affected the fertility decisions of people eg Devirupak in Haryana or the Cradle Baby Scheme in Tamil Nadu. Mother fixed effects, birth order fixed effects and year fixed effects control for the confound factors that could change by mother, birth order and year respectively. The triple difference specification estimated is:

$$
\begin{aligned}
Girl_{bits} &= \beta_0 + \beta_1 Treat_i \times Post_{2006-10,t} \times First\_Girl + \beta_2 Treat_i \times Post_{2011-15,t} \times First\_Girl \\
&+ \beta_3 Treat_i + \beta_4 Post_{2006-10,t} + +\beta_5 Post_{2011-15,t} + +\beta_7 First\_Girl + StateTime_{st} + \delta_i + \lambda_t + \theta_b + e_{bits}
\end{aligned}
$$

While most terms in the above specification are similar to the D-I-D specification, the new addition is $First\_Girl$ which is equal to 1 if the family has first born girl and 0 if it has first born boy. Like previous estimation, our sample continues to be comprised of all families in rural India that started their fertility on or after 2000 and belong to upper caste or OBC and do not fall below the poverty line. The triple difference estimator is β_1 and β_2. The results of this estimation are shown table in 4.

Table 4: Triple Difference Results

	(1) Girl	(2) Girl
Treat×Post$_{2006-15}$×First_Girl	**0.1237****	
	(0.0554)	
Treat×Post$_{2006-10}$×First_Girl		**0.1136****
		(0.0542)
Treat×Post$_{2011-15}$×First_Girl		**0.1802****
		(0.0665)
Treat×Post$_{2006-15}$	-0.0094	
	(0.0471)	
Post$_{2006-15}$×First_Girl	-0.1742***	
	(0.0538)	
Treat×Post$_{2006-10}$		-0.0146
		(0.0449)
Treat×Post$_{2011-15}$		0.0170

		(0.0572)
$Post_{2006-10} \times First\_Girl$		-0.1411**
		(0.0519)
$Post_{2011-15} \times First\_Girl$		-0.3267***
		(0.0645)
StateTime	0.0001	0.0000
	(0.0003)	(0.0003)
Mother FE	Yes	Yes
Time FE	Yes	Yes
Birth Order FE	Yes	Yes
N	62845	62845
r2	0.3788	0.3810
Mean	0.47	0.47
p-value for equality of coefficients		0.02

Standard errors in parentheses clustered at state level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The key coefficients of our interest are the triple difference estimators. The two columns show results with standard errors clustered at state level. Similar to tabel 3, we firt look at the entire post period of the policy from 2006-2015 and then we differentiate between the early and late diffusion period in column 2. The triple difference estimates are larger in magnitude in both the columns. Mothers with first born daughters in treatment group are 11.36 percent more likely to have a girl child at birth in five years after the program was implemented compared to before. The magnitude becomes larger when we compare children born in recent five years to those born before the program. Columns 1 shows the average effect for ten years after the program. These results suggests that one of the unintentional impact of the JSY program is the reduction in sex selective abortions and an increase in probability of girls being born in families eligible for treatment.

7 Robustness checks and falsification test

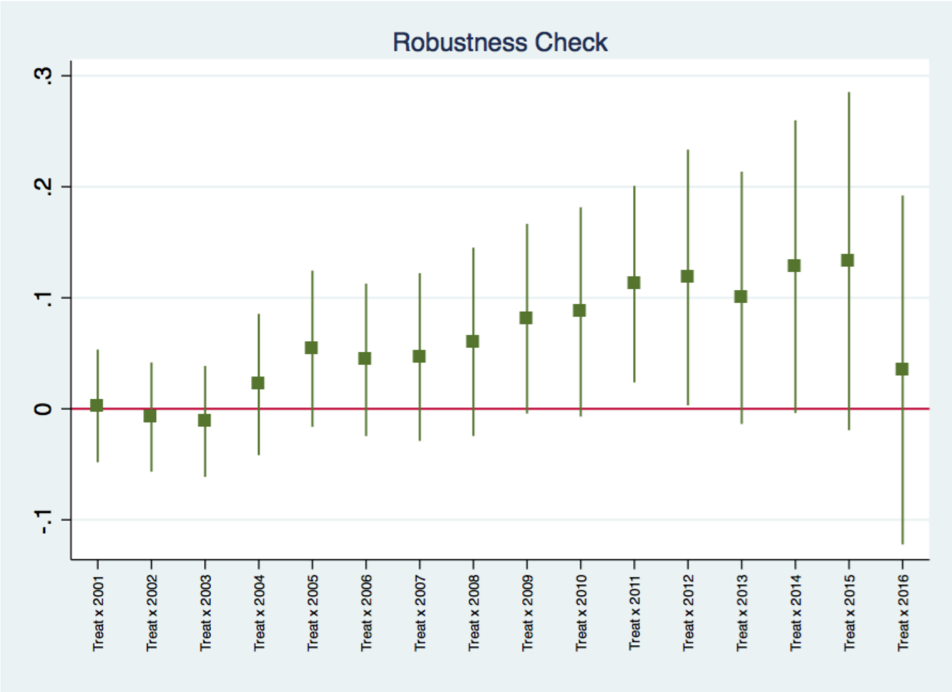
A key assumption of a D-I-D estimation is that the treatment and control groups in the absence of the program should have similar trend. In other words, all the lead years up to the program year should not have any significant effect on the outcome. For us to be confident that program actually had a causal impact on fertility decisions of a mother, we should not observe any significant difference in the probabilities of having a girl or a boy in our treatment versus control groups prior to the program. Significant differences, if any, should only occur after the program if our identification strategy is identifying the program effect. To check this, we estimate the below specification:

$$Girl_{bist} = \beta_0 + \sum_{j=2000}^{2015} \beta_j Treat_i \times Year_j + StateTime_{st}\delta_i + \lambda_t + \theta_b + e_{bist}$$

Figure 4 shows the results of our robustness check estimation. Differences in sex of the children born to mothers in treatment versus control groups are insignificant for all years prior to the year 2005. The differences only become significant after year 2009. The joint test of significance of the leads of the program renders a F-stat of

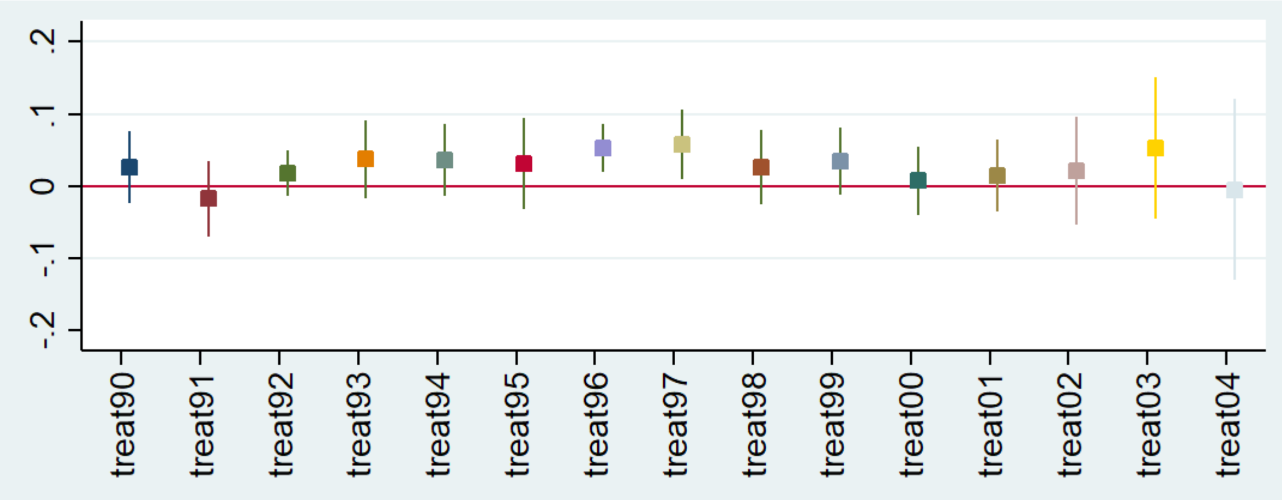
1.26, implying that our identification strategy correctly captures the differences between sex of children caused due to the program.

Fig. 4. Test of non differential pretrends



While are identification strategy is robust we also run some falsification tests. The key idea behind this exercise is that if our empirical strategy identifies the causal impact of the program on the fertility decisions of mothers then we should not be able to see any effect on mothers who never received the program. The first exercise we do is to individually assume each year from 1990 to 2004, i.e. years prior to 2005, to be the program year. Figure 5 plots the coefficient for each year and we can see that the differences in outcomes between the treatment and the control groups is not significant for any year except for 1996 and 1997. One reason why there are significant differences could be due to the structural break in 1995, when the ultrasound technology became widely available in India (Bhalotra and Cochrane [2010], Anukriti [2018], Anukriti et al. [2018]). However, the effect of this structural break does not last long and dissipates after 1997.

Fig. 5. Falsification test assuming program years from 1990 to 2004



The second exercise for our falsification test we run relies on our empirical strategy of Triple Difference on DHS III sample that was collected in 2005-06. Since this survey finished by 2005-06, women interviewed in this sample never received the program. We keep the comparision groups to have the same time length and assume year 1995 to be the program year. One reason for doing this is that if there are any fertility reporting biases for children born more than 10 years ago, then these biases should be the same in the DHS III sample we are using. Hence, if our results are driven by reporting bias then we will also see significant differences in the outcome in our DHS sample.

Like the main estimation, our sample consists of mothers who start their fertility decisions from 1990 onwards. Since we assume 1995 to be the year that the program was rolled out we compare 1990 to 1995 with 1996 to 2000 (our assumed early diffusion period) and to 2001 to 2005 (our late diffusion period). We estimate the below specification:

$$Girl_{bits} = \beta_0 + \beta_1 Treat_i \times Post_{1996-00,t} \times First\_Girl + \beta_2 Treat_i \times Post_{2001-05,t} \times First\_Girl \\ + StateTime_{st} + \delta_i + \lambda_t + \theta_b + e_{bits}$$

Table 5: Falsification Test

	Girl Divided	Girl Combined
Treat×Post$_{1996-00}$×First_Girl	-0.0370	
	(0.0847)	
Treat×Post$_{2001-05}$×First_Girl	-0.0956	
	(0.0952)	
Treat×Post$_{1996-05}$×First_Girl		-0.0491
		(0.0828)
Treat×Post$_{1996-00}$	0.0718	
	(0.0635)	

Treat×Post$_{2001-05}$	0.0981	
	(0.0719)	
Post$_{1996-00}$×First_Girl	-0.0450	
	(0.0326)	
Post$_{2001-05}$×First_Girl	-0.0845**	
	(0.0369)	
Treat×Post$_{1996-05}$		0.0789
		(0.0619)
Post$_{1996-05}$×First_Girl		-0.0547*
		(0.0318)
StateTime	0.0002	0.0002
	(0.0002)	(0.0002)
Mother FE	Yes	Yes
Year FE	Yes	Yes
Birth Order FE	Yes	Yes
N	15524	15524
r2	0.3518	0.3515

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows the results of our falsification test on mothers who started fertility decisions in 1990. The first three coefficients are our triple difference estimators. We can see that all three coefficients are negative and statistically insignificant thereby supporting the causal inference of our estimation strategy. Additional falsification test assuming year 2000 to be the treatment year for the DHS III sample is shown in appendix.

8 Discussion and Additional Evidence

8.1 Impact on infant mortality

The previous section showed the causal impact of JSY on sex selective abortions in India. The program caused an increase in number of girls being born in families eligible to receive treatment, indicating that the mechanisim of access to pre natal sex determination technologies was not dominant and the other three mechanisims had a stronger effect on the fertility decisions regarding sex selection. Previous work has shown that in societies with preference for male children, girls suffer from lower welfare (Jayachandran and Pande [2017]) in families that follow stopping rule and have more girls than they desire. This discrimination is starker for girls at a higher birth orders. In this section we therefore test this hypothesis. We look at the mortality of children born to women in our sample who died after being born at various intervals before age 5. Biologically, mortality among boys is higher than among girls between the age of 0 to 1 (Kraemer [2000]). To compensate for this excess mortality in infant boys, the natural sex ratio is 106 boys per 100 girls.

Using our difference in difference estimator, we test if the the program increased child mortality for girls. Model estimated is:

$$Dead_{ibt} = \beta_0 + \beta_1 Treat_i \times Post_t \times Girl_i + \beta_2 Treat_i + \beta_3 Post_t + StateTime_{st} + \delta_i + \lambda_t + \theta_b + e_{ibt}$$

Table 6 shows the result of above estimation on (i) infant who died before 7 days; (ii) infant who died before 28 days; (iii) infant who died before completing 1 year; (iv) infant who died before completing 3 years; and (v) who died before completing 5 years. For each of these samples, the first two column show results for all infants in rural India irrespective of their birth order. Columns 3 and 4 show results for all infants who were born at birth order greater than 1, i.e. who were not the first born child. The last two columns show results for all infants born at birth order greater than 2. We do this distinction by birth order because girls at a higher birth order tend to die more than boys.

Surprisingly, we find that for all age groups, the probability that the dead infant is a girl is positive at all birth orders. For infants who died under 7 days, we find that probability that the dead infant is a girl, born between 2006 and 2010 and is from the treatment group is 4.2 percent higher than those from control group. While we see no significant differences in probability that the dead infant is a girl if the infant dies under 28 days, The differences are statistically significant when we look at infants that dies under age of 1 year. The statistical significance holds for infant girls that were born at birth order greater than 1 and birth order greater than 2. When looking at all the infant girls born between 2006 to 2015, the statistical significance only holds for girls born at birth order greater than 1. an interesting observation is that the significant difference in mortality between girls and boys disappears when we look at late diffusion period. This could be due to the additional feature of providing nutritional supplements to infants that was added to the program in 2011.

Lastly, we check the pretrends of infant mortality under 3 and under 5 for girls and boys across our treatment and control groups. The joint F-stat of the the leads is 1.59 and 1.33 both of which mean that the pretrends were not different in our preprogram years for girls and boys across treatment and control. We can also see this in figure 8.1.

Table 6: Impact on Infant Mortality

	Dependent Variable= Dead					
	Rural		Rural, bord> 1		Rural, bord> 2	
			Infant Mortality under 7 days			
Treat×Post$_{2006-10}$×Girl	0.0066		0.0093		0.0418*	
	(0.0061)		(0.0070)		(0.0228)	
Treat×Post$_{2011-15}$×Girl	0.0070		0.0162		0.0138	
	(0.0063)		(0.0130)		(0.0299)	
Treat×Post$_{2006-15}$×Girl		0.0067		0.0121		0.0294
		(0.0058)		(0.0081)		(0.0245)
N	150757	152634	63250	64258	23275	23748
r2	0.3645	0.3636	0.4049	0.4041	0.4422	0.4432
Mean	0.026	0.026	0.024	0.024	0.029	0.029
			Infant Mortality under 28 days			
Treat×Post$_{2006-10}$×Girl	0.0090		0.0121		0.0350	
	(0.0064)		(0.0075)		(0.0301)	
Treat×Post$_{2011-15}$×Girl	0.0056		0.0137		-0.0035	
	(0.0072)		(0.0135)		(0.0323)	
Treat×Post$_{2006-15}$×Girl		0.0073		0.0117		0.0174
		(0.0063)		(0.0086)		(0.0291)

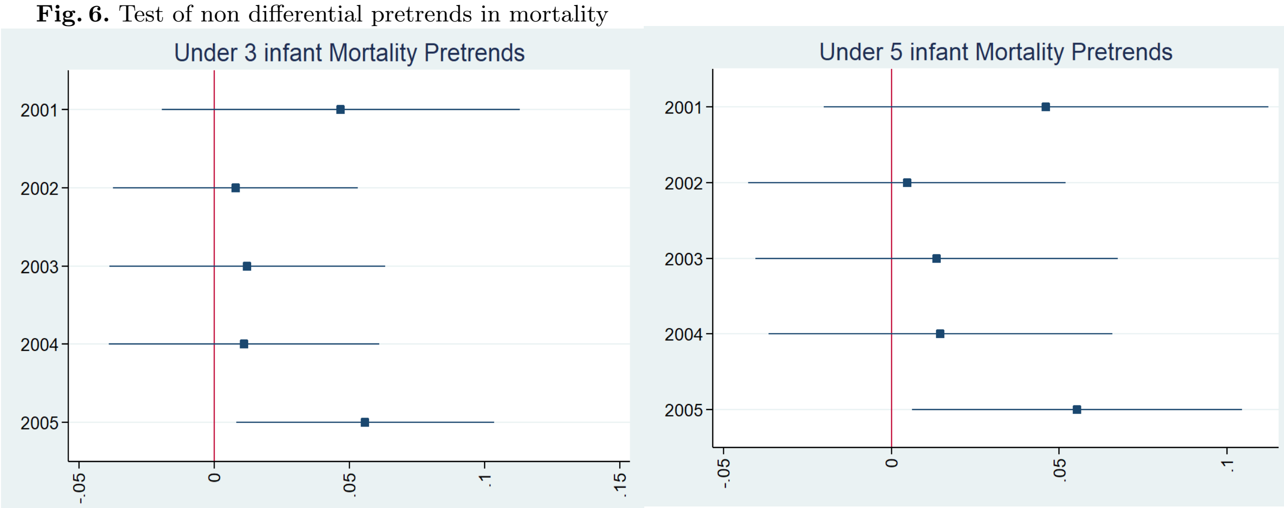
N	150757	152634	63250	64258	23275	23748
r2	0.3698	0.3690	0.4116	0.4112	0.4519	0.4513
Mean	0.03	0.03	0.028	0.028	0.035	0.035
Infant Mortality under 1 year						
Treat×Post$_{2006-10}$×Girl	0.0090		0.0254**		0.0708**	
	(0.0062)		(0.0114)		(0.0274)	
Treat×Post$_{2011-15}$×Girl	0.0054		0.0174		0.0083	
	(0.0079)		(0.0161)		(0.0317)	
Treat×Post$_{2006-15}$×Girl		0.0070		0.0199*		0.0422
		(0.0065)		(0.0115)		(0.0262)
N	150757	152634	63250	64258	23275	23748
r2	0.3675	0.3666	0.4054	0.4044	0.4438	0.4428
Mean	0.042	0.042	0.044	0.044	0.054	0.0254
Infant Mortality under 3 years						
Treat×Post$_{2006-10}$×Girl	0.0098		0.0231*		0.0903***	
	(0.0068)		(0.0119)		(0.0309)	
Treat×Post$_{2011-15}$×Girl	0.0042		0.0117		0.0205	
	(0.0086)		(0.0161)		(0.0323)	
Treat×Post$_{2006-15}$×Girl		0.0070		0.0161		0.0584*
		(0.0071)		(0.0123)		(0.0290)
N	150757	152634	63250	64258	23275	23748
r2	0.3650	0.3639	0.4031	0.4020	0.4416	0.4404
Mean	0.046	0.046	0.047	0.047	0.059	0.059
Infant Mortality under 5 years						
Treat×Post$_{2006-10}$×Girl	0.0201		0.0201		0.0910***	
	(0.0129)		(0.0129)		(0.0301)	
Treat×Post$_{2011-15}$×Girl	0.0085		0.0085		0.0180	
	(0.0154)		(0.0154)		(0.0327)	
Treat×Post$_{2006-15}$×Girl		0.0131		0.0131		0.0578**
		(0.0123)		(0.0123)		(0.0284)
N	63250	64258	63250	64258	23275	23748
r2	0.4022	0.4012	0.4022	0.4012	0.4414	0.4401
Mean	0.047	0.047	0.048	0.048	0.06	0.06

Standard errors in parentheses clustered at state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All regressions include mother, year and birth order fixed effects as well as state time trend

Fig. 6. Test of non differential pretrends in mortality



8.2 Well-being in surviving children

So far we have seen the evidence that JSY program unintentionally caused more girls to be born in treatment families but at the same time increased their probability of death before reaching the age of 5 years. This indicates that the program substituted pre-natal gender discrimination to post natal discrimination among families eligible for the program. While more girls are being born in treatment groups, infant mortality is also high for girls in these families suggesting neglect towards unwanted girls. Work by Anukriti et al. [2018] shows that access to PNSD technologies leads families to not give birth to unwanted girls as a result post natal gender gaps between wanted girls and boys in a family disappear. However, in our case, the program induced families to deffer the discrimination between girls and boys to after they were born. In the previous section we show some evidence that the additional girls being born were unwanted and not cared for which led to a significantly higher probability of these girls dying before the age of 5 years.

In this section we assess the well being of the surviving girls. Widely used measures of child nutrition in literature are the child anthropometrics. Child anthopometric indicators are are derived from physical body measurements, such as height or weight (in relation to age and sex). While weight and height based on age and sex of the child do not indicate malnutrition directly as they are affected by many intervening factors other than nutrient intake, in particular genetic variation. However, even in the presence of such natural variation, it is possible to use physical measurements to assess the adequacy of diet and growth, in particular in infants and children. This is done by comparing indicators with the distribution of the same indicator for a "healthy" reference group and identifying "extreme" or "abnormal" departures from this distribution [O'donnell et al., 2008]. The new reference population recommended by WHO is based on random samples form US population reflecting ethnic diversity among mothers following prescribed health behaviour eg. breastfeeding, no smoking etc.

The most common way of using these measures is to convert them in to z-scores. The three most commonly used indicators for assessing child level nutrition are (i) Height-for-age z-score (HAZ); (ii) Weight-for-age z-score (WAZ); and (iii) Weight-for-height z-score (WHZ). WAZ is used to monitor growth and change in malnutrition over time, HAZ on the other hand reflects cumulative linear growth and indicates past inadequate nutrition or chronic illness. Lastly, WHZ is the indicator for current nutritional status and is used to screen infants/children at risk and identify short term changes in nutritional status. To compute these z-scores, we follow the latest process prescribed by WHO and also used by Jayachandran and Pande [2017].

DHS IV collects information on these child level anthropometric indicators for all children between the age of 0 to 5 years who agree to be measured and are present at the time of the survey. Our sample consists of 237,508 children who were measured in the survey and are from rural population. This enables us to create all the above three measures to test the well-being of the surviving children in our sample. There are however, some drawbacks of this analysis. First, in our sample many mothers have no more than one child below the age of 5 years, as a result we can no longer use mother fixed effects in our regression. And second, since the children between the age of 0 to 5 are all those born in the late diffusion phase we do not have a counter factual sample to compare their outcomes to. As a result we are only able to compare the outcomes between our treatment and control groups and hence these results should not be interpreted as the causal effect of the JSY program. This analysis is only meant to provide additional evidence to what are the possible child level outcomes as a result of changes in fertility decisions caused by the program. The specification estimated is:

$$Ybits = \beta_0 + \beta_1 Girl_{bi} \times Treat_{is} + \beta_2 Girl_{bit} + X_{its} + \delta_i + \lambda_t + \theta_b + e_{bits}$$

Where the dependent variable is either of the three z-scores for child at birth order b born to mother i at time t in state s. $Girl_{bit}$ is the dummy variable which equals one if child is a girl. $Treat_{is}$ is the same variable as before that captures if the child is from a family eligible for treatment or if he/she is from the control group family. Lastly, X_{its} is a vector of mother and household level controls. Estimation is done with standard errors clustered at the mother level since we are unable to control for mother level heterogeneity. Table **??** below compares child level anthropometic outcomes for the surviving children who are less than 60 months of age in our sample. We consider all three child anthomopetric z-scores discussed above.

Table 7: Child anthropometric outcomes

	HAZ	WAZ	WHZ
Girl	0.0857***	0.0719***	0.0473***
	(0.0266)	(0.0224)	(0.0169)
Girl×Treat	-0.0584*	-0.0598**	0.0004
	(0.0309)	(0.0274)	(0.0230)
Mom Age	0.0862***	0.0635***	-0.0081
	(0.0158)	(0.0094)	(0.0152)
Mom Age Sq	-0.0009***	-0.0006***	0.0001
	(0.0003)	(0.0002)	(0.0003)
Mom Education	0.0294***	0.0247***	0.0092***
	(0.0039)	(0.0019)	(0.0026)
Age at First Birth	-0.0216***	-0.0191***	-0.0004
	(0.0049)	(0.0040)	(0.0043)
Total Eligible Women	0.0142*	0.0186***	0.0121**
	(0.0082)	(0.0054)	(0.0050)
Wealth	0.1442***	0.1331***	0.0625***
	(0.0108)	(0.0106)	(0.0124)
StateTime	-0.0017	-0.0021***	-0.0011
	(0.0010)	(0.0006)	(0.0015)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Birth Order FE	Yes	Yes	Yes
N	64209	65240	63476

r2	0.1035	0.1049	0.0340

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First column of table ?? shows the results for height-for age measure. We see that the height-for-age outcome is much worse if the child is a girl in the treatment group versus if it is a boy. Similar results hold for weight-for-age. magnitude of the effects are almost similar in both cases. On average, a girl child is the treatment group is likely to be shorter and thinner than a boy of her age by 0.06 standard deviation points. we find no significant differences across boys and girls when we look at WHZ.

These results, indicate that gender gaps in well-being continue to exist among the surviving children with girls having poorer health outcomes than boys their age in the sample. Given the non-causal nature of this analysis and to find policy relevant results, in the next part we look at how these gaps change at different points in the overall distribution of the outcome.

8.3 Heterogeneity in child level outcomes

In this section we explore the heterogeneity in child anthropometric outcomes for all surviving children in our sample that are born on or after 2010. In the previous section, we only concentrated at the mean or the average effect of covariates on child level outcomes. However, from a policy perspective, we are more interested in how these covariates affect the lower and upper tails of the distribution. In other words, this section answers the question: "for the families eligible for the program, are the child level outcomes different for children on the lower end of the distribution than those with average outcomes?".

Like the previous section, analysis in this section is limited to those currently living children who were born after 2010 and are between the age of 0-5 years. The dependent variable is height-for-age Z-score and weight-for-age Z-score. All dependent variables are the same as those used in the previous section. Table 8 shows the results for quantile regression for height for age Z score. The key variable of interest is Girl $\times$ Treat that measures the difference in height for age outcomes for girls born in treatment group with those born in the control group. We find that while the height for age for girls in treatment group is lower than those in control group at all quantiles, the difference is statistically significant for girls in second and third quantiles. So girls at second quantiles from treatment group have height for age 0.085 standard deviation points lower than those in the control group. Similarly, for girls at median from the treatment group have height for age 0.06 standard deviation points lower than those in the control group. On comparing these results with liner regression estimates presented in table ?? we can see that estimates from linear model underestimate the effect for second quantile while overestimating the effect at fourth and fifth quantiles.

Table 8: Child HAZ quantile outcomes

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
Girl	0.0798**	0.1057***	0.0498*	-0.0111	0.0531
	(0.0387)	(0.0283)	(0.0260)	(0.0334)	(0.0532)

Treat	-0.3797**	-0.1107	0.0447	-0.2804*	-0.2236
	(0.1707)	(0.1246)	(0.1145)	(0.1473)	(0.2344)
Girl × Treat	-0.0194	-0.0846**	-0.0599**	-0.0265	-0.0265
	(0.0455)	(0.0332)	(0.0305)	(0.0393)	(0.0625)
Mom Age	0.0922***	0.0925***	0.0879***	0.0727***	0.1149***
	(0.0207)	(0.0151)	(0.0139)	(0.0178)	(0.0284)
Mom Age Sq	-0.0010***	-0.0009***	-0.0009***	-0.0006**	-0.0013***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Mom Education	0.0388***	0.0356***	0.0319***	0.0276***	0.0212***
	(0.0026)	(0.0019)	(0.0017)	(0.0023)	(0.0036)
Age at First Birth	-0.0293***	-0.0287***	-0.0206***	-0.0181***	-0.0141
	(0.0062)	(0.0046)	(0.0042)	(0.0054)	(0.0086)
Total Eligible Women	-0.0212*	-0.0018	0.0074	0.0217**	0.0396**
	(0.0118)	(0.0086)	(0.0079)	(0.0102)	(0.0162)
Wealth	0.1898***	0.1794***	0.1646***	0.1416***	0.0856***
	(0.0105)	(0.0077)	(0.0071)	(0.0091)	(0.0145)
Intercept	-4.7762***	-4.2349***	-3.4683***	-2.0418***	-1.5553***
	(0.3206)	(0.2339)	(0.2149)	(0.2766)	(0.4401)
State Controls	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes
Birth Order Controls	Yes	Yes	Yes	Yes	Yes
N	64209	64209	64209	64209	64209

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7 presents a visual summary on quantile regression results. Each plot depicts the nine coefficient in the quantile regression model. The solid line represents point estimates for coefficients for all percentiles ranging from 0.05 to 0.095. The shaded grey area represents a 90 percent pointwise confidence band. Superimposed on the plots is the dashed line representing the ordinary least square estimate of the mean effect, with two dotted lines representing the 90 percent confidence interval for this coefficient.

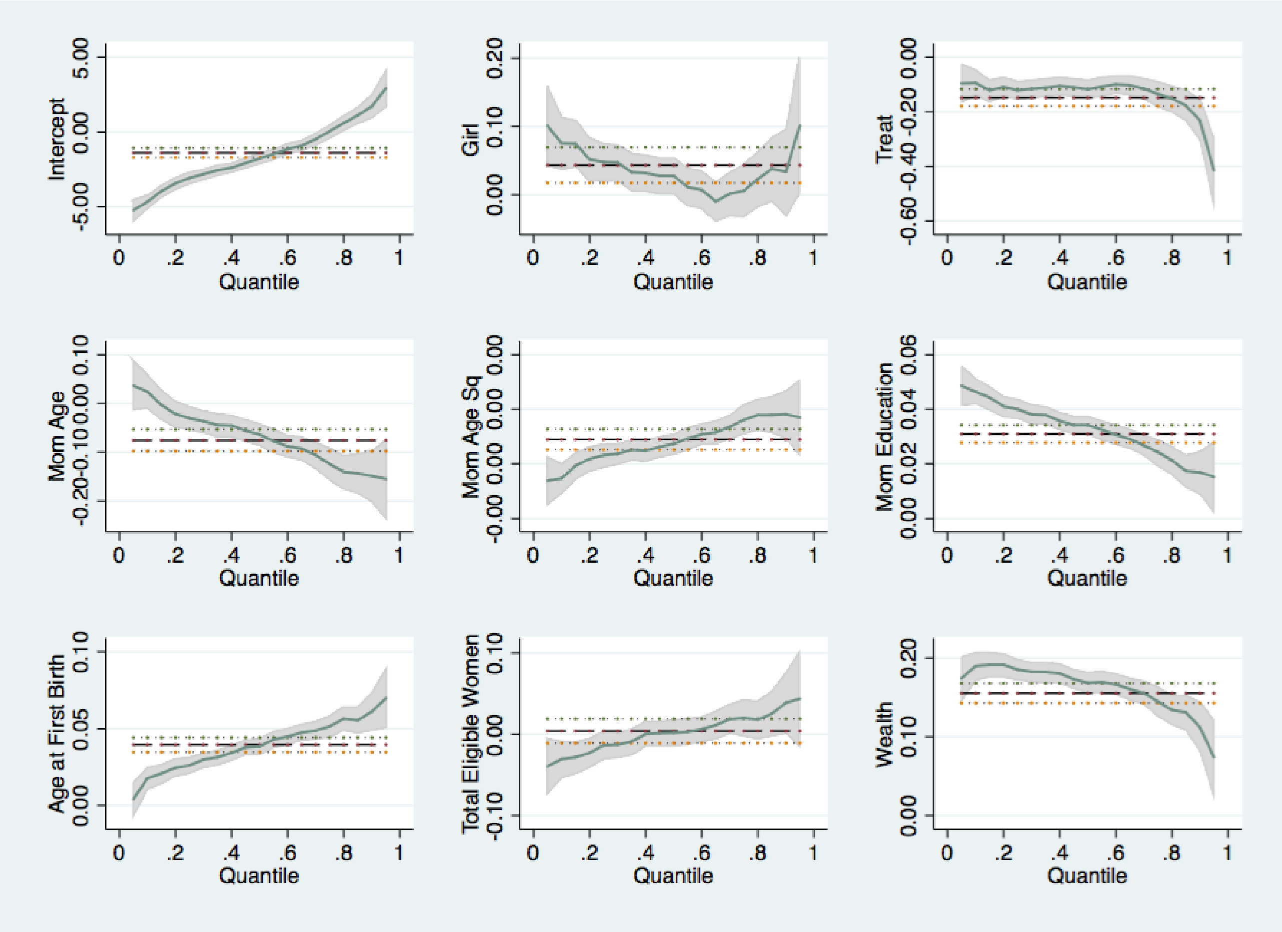


Fig. 7. Child Height-for-Age Z Score Quartiles

Similar to table 8, table 9 shows the results of fixed effects quantile regressions for weight for age for all surviving children aged between 0 to 5 years in our sample. Again, the key variable of interest is Girl × Treat that measures the difference in weight for age outcomes for girls born in treatment group with those born in the control group. We can see that for most of the quantiles, weight for age for girls in treatment group is lower than those in control group versus boys in these groups except for in the fifth quantile. These differences are statistically significant and increase in magnitude with each quantile. On comparing quantile outcomes with those from linear regression results in table **??**, we can see that mean results underestimate the impact for children in first, third and fourth quantile. Figure 8 visually depicts the impact of each of the covariates on the distribution of weight for age across the sample distribution.

The above analysis shows that while the child level outcomes for families eligible for the JSY program are worse for girls than boys, the effect is more detrimental for girls in the lower end of the distribution

Table 9: Child WAZ quantile outcomes

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
Child_sex	0.1278***	0.0822***	0.0658***	0.0534**	-0.0280
	(0.0328)	(0.0229)	(0.0209)	(0.0225)	(0.0304)
Treat	0.1928	0.2156**	0.2320**	0.2766***	-0.0074
	(0.1448)	(0.1013)	(0.0923)	(0.0995)	(0.1342)
Child_sex × Treat	-0.0691*	-0.0617**	-0.0630**	-0.0760***	0.0087
	(0.0385)	(0.0269)	(0.0245)	(0.0264)	(0.0357)
Mom Age	0.0794***	0.0639***	0.0506***	0.0480***	0.0546***
	(0.0175)	(0.0122)	(0.0111)	(0.0120)	(0.0162)
Mom Age Sq	-0.0009***	-0.0007***	-0.0005***	-0.0004**	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Mom Education	0.0268***	0.0277***	0.0248***	0.0228***	0.0220***
	(0.0022)	(0.0015)	(0.0014)	(0.0015)	(0.0020)
Age at First Birth	-0.0251***	-0.0217***	-0.0160***	-0.0132***	-0.0167***
	(0.0053)	(0.0037)	(0.0034)	(0.0036)	(0.0049)
Total Eligible Women	0.0175*	0.0191***	0.0152**	0.0145**	0.0312***
	(0.0100)	(0.0070)	(0.0064)	(0.0069)	(0.0093)
Wealth	0.1486***	0.1389***	0.1380***	0.1326***	0.1193***
	(0.0089)	(0.0062)	(0.0057)	(0.0061)	(0.0083)
Intercept	-4.6985***	-3.7499***	-2.8986***	-2.1997***	-1.3947***
	(0.2711)	(0.1895)	(0.1728)	(0.1861)	(0.2512)
State Controls	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes
Birth Order Controls	Yes	Yes	Yes	Yes	Yes
N	65240	65240	65240	65240	65240

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

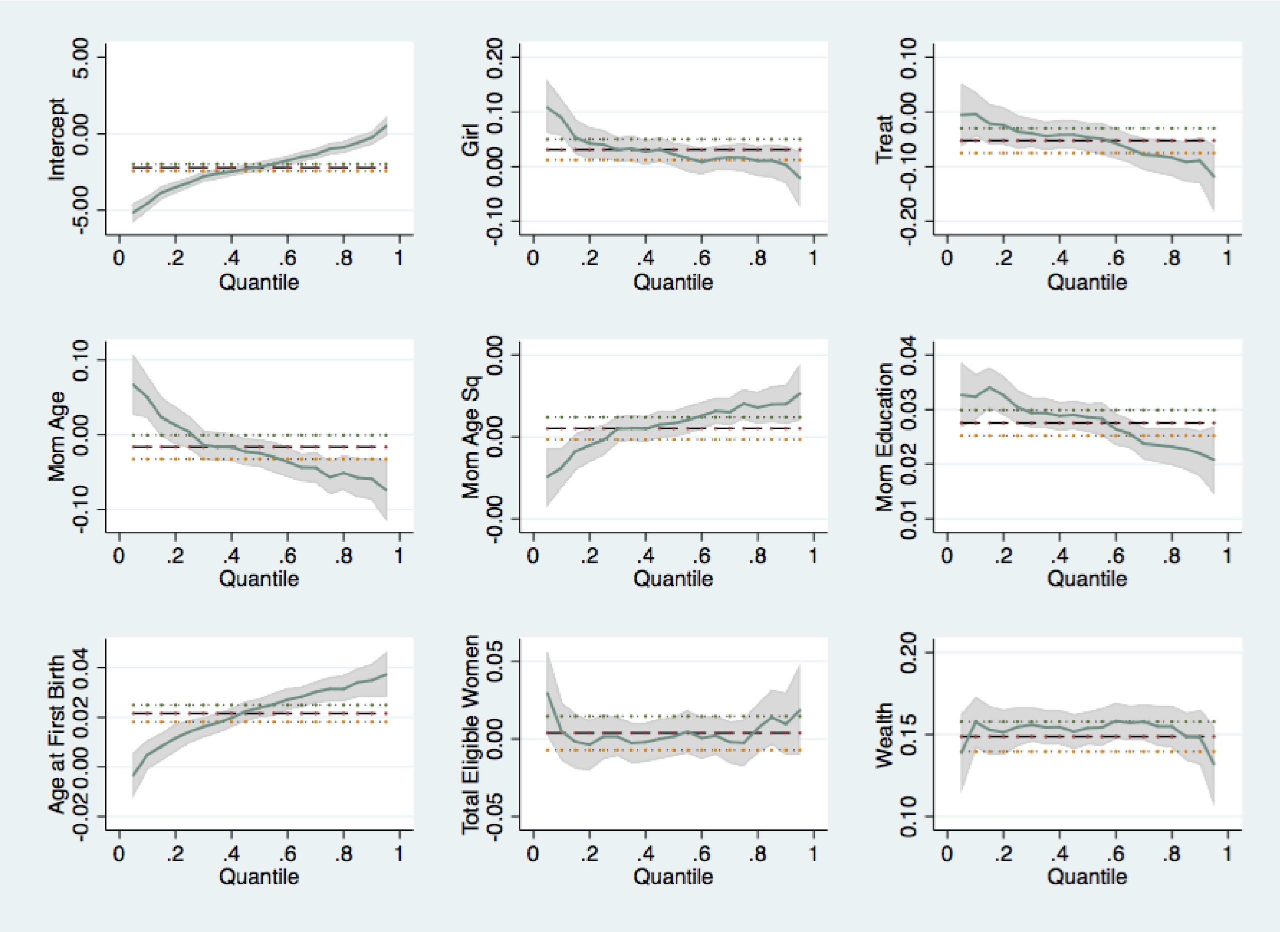


Fig. 8. Child Weight-for-Age Z Score Quartiles

9 Conclusion and policy recommendation

This paper examined the impact JSY conditional cash transfer program had on fertility decisions of mother in rural India. More specifically, it tested the if a program that increased the usage of health services that could be used for pervasive sex selection and a cash transfer on live birth could possibly have an impact on parental sex selective behaviour. We see that, contrary to the previous literature this program increased the probability of having a girl at each birth order. The magnitude is especially larger in families who according to the literature have a greater incentive to sex select i.e those whose first child is a daughter.

While this result is encouraging at the first glance a further analysis on their survival shows that within the families eligible for treatment, infant mortality is likely to be higher for girls than boys specifically at higher birth orders, indicating the shift of gender discrimination from prenatal to post natal, an outcome that the program hopes to fight against. The results seem to suggest that families at the margin preferences are related to discrimination channel choice for households. Lastly, among the surviving children we find that girls on average have lower nutritional status than boys their age and this gender gap is highest for children on the lower end of the distribution.

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A Appendix

A.1 Exogeneity of the first born (Bhalotra et al 2018)

Table 10: Impact on sex of first child

	(1) First_Girl1990-2000	(2) First_Girl2000-05
Years of schooling	0.0047***	0.0006
	(0.0007)	(0.0006)
Muslim	-0.0196***	0.0051
	(0.0069)	(0.0076)
Christian	0.0176	-0.0014
	(0.0184)	(0.0334)
Sikh	0.0360**	0.0244
	(0.0145)	(0.0275)
Buddhist	-0.0087	0.0133
	(0.0383)	(0.0374)
Jain	0.0691	-0.0700
	(0.0697)	(0.1166)
ST	-0.0215	0.0469
	(0.0264)	(0.0366)
OBC	0.0033	0.0062
	(0.0171)	(0.0205)
Forward_caste	0.0056	0.0098
	(0.0163)	(0.0229)
Number_of_eligible_women_inhousehold	0.1437***	0.0591***
	(0.0150)	(0.0081)
Household_head_sex	0.0184**	0.0026
	(0.0075)	(0.0095)
Household_head_age	-0.0007**	-0.0005
	(0.0003)	(0.0004)
Wealth_Index	-0.0155***	-0.0092***
	(0.0025)	(0.0028)
Electricity	0.0234***	0.0173
	(0.0086)	(0.0110)
Radio	-0.0054	0.0076

	(0.0083)	(0.0087)
TV	-0.0048	-0.0055
	(0.0087)	(0.0080)
Refrigerator	0.0045	-0.0123
	(0.0093)	(0.0124)
Bicycle	0.0040	-0.0458***
	(0.0064)	(0.0069)
Scooter	-0.0621***	-0.0001
	(0.0064)	(0.0057)
Car	0.0229***	0.0279**
	(0.0073)	(0.0125)
strend	-0.0000	-0.0001
	(0.0001)	(0.0002)
N	35295	26255
r2	0.0729	0.0111
State FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Here we regress firstborn sex on indicators for post-Janani Suraksha Yojana cohorts and various controls (state fixed-effects, state-specific linear time trends), and find that it is not significantly predicted by these variables.

Table 11: Impact on sex of first child of Post variable

	(1)
	fg2
$\text{Post}_{2006-10}$	-0.0023
	(0.0046)
$\text{Post}_{2011-15}$	-0.0096
	(0.0087)
strend	0.0000
	(0.0000)
N	78730
r2	0.0006
State FE	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Additional Robustness Check and Evidence

We support our causal estimation obtained from difference in difference by carrying out double robust estimation where we model both the propensity score and the conditional mean outcome. Double robust estimators remain consistent even if any one of the models (but not both) are mispecified [Słoczyński and Wooldridge, 2018]. For this estimation we restrict our sample to mothers who began their fertility after 2005 i.e after the program was put in place. The treatment group is mothers belonging to upper caste, non BPL categories in the low performing states and the control group is mothers belonging to upper caste, non BPL categories in the high performing states. Even if the sample considered for DR-estimation is different from the original sample considered for the D-I-D estimation, the results obtained support our hypothesis and provide further evidence for our story. The policy led to an increased probability of a girl child being born to parents in the treatment group increasing also their fertility level by 0.17 on average. We hypothesize that parents were more likely to follow son biased stopping rule and an average child would have an increased number of girl siblings.

B.1 Doubly Robust Estimation

From Table 12, we see that average causal effect of the program on the probability of being a female child is is positive, however insignificant for the treatment households who began their fertility after 2005.

Table 12: Impact of the policy on the sex of the child

	(1) Girl
ATE	0.0033
	(0.0061)
N	95258
r2	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Impact on Fertility

The program led to an increase in the number of children born to mothers in the treatment group after 2005.

Table 13: Impact of the policy on fertility

	(1) Number of children
ATE	0.1736***
	(0.0107)
N	51549
r2	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Sibling Size

The number of girl siblings every child has on average in the treatment group is positive and significant.

Table 14: Impact of the policy on the number of girl siblings every child has

	(1)
	Number of girl siblings
ATE	0.1367***
	(0.0087)
N	95258
r2	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 sex of the last child more likely to be male in LPS

From Table 15, we see that average causal effect of the program on the probability of the last child being a girl in the treatment group is negative and significant.

Table 15: Impact of the policy on the sex of the last child

	(1)
	Girl
ATE	-0.0209***
	(0.0073)
N	51549
r2	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Additional Falsification Test

Table 16: Falsification Tests Comparing 1995-1999 with 2000 - 2005

	(1)	(2)
	M1	M2
Treat × Post	0.0282	0.0282
	(0.0441)	(0.0532)
Post × First_Girl	-0.0395	-0.0395
	(0.0255)	(0.0263)

Treat× Post × First_Girl	-0.0517	-0.0517
	(0.0410)	(0.0671)
StateTime	-0.0000	-0.0000
	(0.0006)	(0.0003)
Mother FE	Yes	Yes
Year FE	Yes	Yes
Birth Order FE	Yes	Yes
N	11987	11987
r2	0.3846	0.3846

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$