Student Paper

Young Lives

"A Healthy Mind in a Healthy Body": The Economic Causes and Consequences of Gender Bias in the Allocation of Healthcare during the Early Stages of Life

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Thesis submitted in part fulfilment of the requirements for the degree of MSc in Economics for Development, University of Oxford.

The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam over a 15-year period. www.younglives.org.uk

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Abstract

The so-called "fetal origins hypothesis" has increased the interest of health economists in the importance of the environment during the first 1,000 days of life following conception. Economists have found growing evidence that the lifelong trajectory of human capital formation is strongly governed by the level of healthcare that children receive during this time period. This essay follows recent literature in asking how gender-biased investments in early-life healthcare can affect long-term educational outcomes for boys and girls. Focusing on India, where the Young Lives longitudinal study allows for following a cohort of children over a 12-year period, these data are used to first establish the relationship between early-life health and cognitive development, and then search for potential gender biases in early-life healthcare. Under a certain set of assumptions, and following previous literature on household behaviour in India, I am able to construct a sample whereby I can identify if the sex of the fetus has likely been determined, thus allowing for potential gender preferences to influence resource allocation decisions. This essay, inclusive of OLS, 2SLS and logit regression analysis, forms a solid case for a differential in educational attainment between the genders driven by early-life healthcare.

Young Lives is an international study of childhood poverty, following the lives of 12,000 children in 4 countries over 15 years (www.younglives.org.uk). Young Lives is core-funded from 2001 by UK aid from the UK Department for International Development (DFID) and co-funded by Irish Aid from 2014. The views expressed are those of the author. They are not necessarily those of, or endorsed by, Young Lives, the University of Oxford, DFID or other funders.

Data remains anonymised to do account for its sensitive nature and to protect participants.

Contents

Introduction: A Literature Review

There is a well established literature on the effect of the composition of early-life healthcare on economic outcomes such as cognitive development, human capital, and ultimately wage earning ability (Currie et al, 2010; Fogel, 2012; Heckman, 2007; Horton and Ross, 2012). Furthermore, many scientific and economic studies on the early-life environment have positioned themselves around the 'fetal origins' hypothesis (Barker, 1990), and focus on the prenatal time period. This attention stems from the controversy surrounding the hypothesis, as it opposed the traditional notion that a fetus is a "perfect parasite" that is resistant to negative shocks *in utero* (Susser and Stein, 1994, in Almond and Currie, 2011). Barker's prominent article, "The Fetal and Infant Origins of Adult Disease", implies that it would serve economists well to view the prenatal and infant stages of life as one critical time period of human capital formation, and thus as a target for policy intervention. Investigation of what Almond and Currie describe as the "nonhealth endpoints" of early-life epidemiological phenomena has brought the concept of the "first 1,000 days" (UNICEF, 2016) into key development strategies. It is clear that female agents are naturally bestowed with a crucial role in this story. Moreover, country specific incumbent social norms concerning gender can result in underinvestment in the female proportion of the population (Fikree and Pasha, 2004). Through the mechanisms described above, this implies a gender discrepancy in the formation of capabilities, and one that will manifest over generations due to the dynamic and positive relationship between health and education. The "first 1,000 days" which is becoming a familiar concept in the development sphere, must be integrated with the Sustainable Development goals (SDG) for gender equality and the reduction of inequality.

The Young Lives data include seven variables of interest that cover both prenatal and infant healthcare investment in India. They account for the receipt of tetanus injections by the mother and any iron supplements during pregnancy, the take up of a food nutrition programme for the infant, plus the child's receipt of essential vaccinations. One factor that influences a child's cognitive development path is the existence or avoidance of iron deficiency during pregnancy. The WHO (1994) estimates that more than 30% of pregnant women in developing countries suffer from iron-deficiency anaemia. As a result, children born to anaemic mothers are likely to have lower iron stores and develop iron deficiency sooner. Following this analysis, the lack of prenatal iron supplements has contributed towards more than 75% of toddlers being anaemic (Pasricha et al., 2010). Iron deficiency during infancy, at both moderate to severe levels, appears to cause permanent neurological damage (Scrimshaw and Gordon 1968; Chávez et al., 1995, in Fogel, 2012). The mechanism by which a lack of iron impairs cognitive function is not fully understood, however it has been demonstrated to be essential for neurotransmitter production and normal brain development (Lozoff, 2000). De Ungria et al. (2000) present the hypothesis that "perinatal iron deficiency would differentially reduce neuronal metabolic activity in areas of the brain involved in memory processing" (Lozoff, 2000) – obviously a key capability required for skill formation and success in education. In terms of measurable outcomes, observational studies show that "infants with moderate iron deficiency anemia have test scores that are 0.5 to 1.5 standard deviations lower than those of infants with sufficient iron stores" (Lozoff 1988; Pollitt, 1993, in Horton and Ross, 2012). Adequate iron intake can be achieved through both direct supplementation and the nutrition that food provides, thus the two prenatal variables for iron supplements and the postnatal variable for the uptake of a food nutrition programme are relevant for this analysis. A particular concern is that iron-rich foods tend to be protein based, which in turn, tend to be relatively expensive and consumed less compared to the staple, starchy foods in developing countries.

Tetanus vaccinations for a pregnant women go some way in reducing the mortality risk from maternal and neonatal tetanus. Children who are lucky enough to survive neonatal tetanus (NNT) show evidence of "mild neurological abnormalities, developmental impairment – particularly fine motor difficulties – and behaviour problems" (Barlow et al., 2001). Similarly, postnatal disease prevention through the immunisation of children contributes positively to cognitive development by increasing school attendance and the avoiding the negative shock of disease during critical neurocognitive development stages. Bloom et al. (2012) find that "full childhood vaccination for measles, polio, Tuberculosis (TB), Diphtheria, Pertussis and Tetanus (DPT) significantly increases cognitive test scores." By matching children through a propensity score to account for the endogeneity of the positive effect of mother's education on both the healthcare uptake and child's cognitive outcomes, they find that the effect of full immunization compared to no vaccinations is around half a standard deviation of test scores. Bloom et al. also highlight the fact that propensity matching cannot account for unobservable characteristics, and this must be considered when interpreting their results. In the following section of this essay I attempt to account for unobservable characteristics such as inherent intelligence of the mother through an instrumental variable approach.

Linking cognitive development to long run economic outcomes, Horton and Ross (2012), pair together the estimations of the effects of iron deficiency on cognitive score outcomes with the literature concerning cognitive scores and their relationship with wages. Their analysis can be extended to any of the health variables from the critical early-life period. While allowing for the joint determination of schooling and cognitive skills, and accounting for selection bias (a measure of wages being only a representative sample of those that have been selected into employment, rather than the whole population), Alderman et al. (1996, in Horton and Ross, 2012) find a 12 percent increase in wages from a one-standard deviation cognitive score improvement. Obviously, this will be context specific to their study of Pakistani rural labour markets, but a similarly positive relationship is expected for India, if not of the exact estimated magnitude. Furthermore, as Glewwe (2002) notes, there aren't any clear gains from cognitive development for the workers in agriculture that are self employed. However, the structural transformation that accompanies economic growth (Herrendorf et al., 2012) calls for a greater emphasis on the importance of human capital and, hence, cognitive skills. This wage effect is indeed relevant for India's formal sector currently, but even more so for future generations, conditional on the economic development path.

"A lifecycle investment framework is the foundation for understanding the origins of human inequality and for devising policies to reduce it" (Heckman, 2007). Thus, I take the above investment framework in human capital through healthcare in the first 1,000 days of the lifecycle to better understand inequity in terms of gender[1]. Stemming from unequal treatment of women, justified and reinforced by cultural and social norms and traditions in India, I argue that there is negative feedback between expected wages on health investment in female offspring. This denies these agents of reaching their optimal neurocognitive development and hence productivity, that in turn, dampens their income according to the process exhibited by Horton and Ross (2012). Many studies show that a gender wage gap is prevalent throughout

[1] Throughout this essay gender is assumed to correspond to biological sex, and the two terms are used interchangeably.

the economy (Madheswaran & Khasnobis, 2007). A simple utility maximization problem can illustrate how gender discrimination will perpetuate and be exacerbated throughout time, even if beliefs surrounding differences in the capabilities of men and women have changed. Assuming that rational agents form their expectation of future wages based on past trends, and these wages form the basis of rational decision making by households wishing to allocate early-life healthcare investments, scarce resources will go to a child of the sex expected to bring in the most income. A case for disparities in health investment based on the internal cost-benefit analysis made by those who allocate household resources may be more visible in India as "sons are perceived to have economic, social, or religious utility; daughters are often felt to be an economic liability because of the dowry system" (Arnold et al., 1998, in Fikree, and Pasha, 2004). This 'return on investment' from a child of a particular gender is pitted against the opportunity cost in terms of time lost from labour travelling to and attending healthcare clinics, plus the direct costs of obtaining supplements and medicine if they are not provided by the state. If the expected pay-off exceeds the costs of health investment, the mother will engage in the treatment her herself and her child.

The literature indeed reinforces this notion that girls in India are receiving less healthcare investment than boys in the first 1,000 days of their lives. In an econometric study of the vaccinations between the ages of one and two of 4,000 children in India, "the likelihood of girls being fully vaccinated, after controlling for other variables, was 5 percentage points lower than that for boys" (Borooah, 2004). Also in this paper, Borooah demonstrates than when mother's are illiterate, "girls were 5 percentage points less likely to be well-fed relative to their brothers" (ibid). Borooah estimates two separate logit models for male and female children and uses these to estimate probabilities of a child receiving the two types of healthcare. Each logit is modelled with a "vector of determining variables", where as I will incorporate the dummy variable for sex into one model, and control using an analogous, but more concise set of controls to avoid multiple correlation.

Methodology

Implementing an instrumental variable approach and a logistical regression analysis respectively, this essay will utilize the Young Lives longitudinal dataset in an attempt to establish the existence of:

(i) a positive effect of early-life healthcare on long-term cognitive outcomes.

(ii) a gender bias in the allocation of the early-life healthcare.

Although the first relationship is well established in the literature, it is worthwhile to determine whether this is true for this context before uncovering a story of gender biases. Thus, from a policy making perspective, the argument concerning the importance of ensuring optimal and equal investment in early-life healthcare in India will be clearer.

Econometric Analysis: Early-Days Health on Cognitive Outcomes

Table 1

Summary statistics: the dependent variables I					
Variable (S_{ij})	n	Mean	S.D.	Min.	Max.
Highest School Grade (S_{i1})	1432	6.46	1.16	1	10
PPVT Score Age 5 (S_{i2})	1851	27.45	21.12	3	119
Cognitive Score Age 5 (S_{i3})	1927	9.39	2.6	0	14
PPVT Score Age 8 (S_{i4})	1901	58.49	30.45	10	186
Math Score Age 8 (S_{i5})	1904	12.03	6.42	0	29
Reading Score Age 8 (S_{i6})	1915	5.42	3.38	0	14
PPVT Score Age 12 (S_{i7})	1902	43.07	7.84	2	57
Math Score Age 12 (S_{i8})	1857	12.77	6.6	0	28
English Score Age 12 (S_{i9})	1862	13.6	4.39	0	22
Language Score Age 12 (S_{i10})	1858	13.39	4.48	0	24

The Data

In the Young Lives longitudinal study, the ‘younger cohort’ of children in India (Andhra Pradesh and Telangana) comprises of around 2,000 observations of children at one year of age in 2002, with rounds of data collected again once they are 5, 8, and 12 years of age. It is only for the ‘younger cohort’ that observations of prenatal and infant healthcare are included, therefore it is only this cohort which will be used in each stage of the empirical analysis. For the first section of empirical analysis I use seven indicators of cognitive development to cover a broad range of critical skills key for determining wage earning ability.

Table 1 presents the summary statistics for the dependent variables for this initial empirical analysis[2]. The differences in observations are due to cases when the conditions are unsuitable for the children to take the tests, e.g. bad lighting. There is also attrition over the course of the Young Lives study. However, this is not of a magnitude that requires concern. Around 1.5 percent of the attrition in the Young Lives sample at least from rounds two to three is accounted for by mortality, which we can assume is a similar case between all four of the rounds. However, as mortality will be related to and agent’s stock of health, this is another potential cause of economic loss to bear in mind as a consequence of underinvestment in early-life healthcare.

The Young Lives data are “highly clustered” (Dercon and Singh, 2011), and I account for this by clustering the standard errors by communities (of which there are around 90 in the Young Lives sample). This is assuming that there will be within-community correlation of cognitive ability due to communities sharing the same schools, and thus receiving the same quality of teaching provided by these schools. Furthermore, Kumra (2008) found that households in the

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[2] All scores reported for the tests are the raw scores (See Young Lives Data Dictionaries). PPVT Score refers to the, Peabody Picture Vocabulary Test. The cognitive test is the Cognitive Developmental Assessment (CDA) test. The ‘Highest School Grade’ is the highest school grade that child has reached regardless of if they are still in the education system or not. Other variables are self explanatory.

Young Lives sample are slightly wealthier than the average household for Andhra Pradesh in the national Demographic and Health Surveys (DHS) Programme. However, this may be attributable to fluctuating poverty rates between the dates of these surveys, and as the Young Live sample covers the diversity of children in the geographical area, they are valuable data for analysing causal relations (Kumra, 2008).

The Model: Instrumental Variables Estimation

The choice to use an instrumental variable approach is based, firstly, on the heritability of genetics that determine intelligence (Neisser et al., 1996), and thus the endogeneity of the binary healthcare variable in each model. Those women with a higher level of intelligence are more likely to be aware of the benefits of good healthcare during pregnancy and the child's infancy, and so will tend to pursue a good level of care for themselves and the child. This means that due to the unobservable genetic traits that determine intelligence, the OLS estimate of the coefficient on the healthcare variable will be biased upwards. As Neisser et al. propose that the heritability of intelligence increases from infancy to childhood, the endogeneity problem is exacerbated as the child ages. They estimate that the order of heritability stands at 0.45 in childhood, increasing to 0.75 by late adolescence. Thus, *ceteris paribus*, we would expect the OLS estimates for the cognitive scores at age five to look more similar to the 2SLS coefficient estimation than the estimates for cognitive tests taken at age 12 years.

Furthermore, Garrido (2009) highlights three selection processes that may bias the observed relationships between prenatal care and long term outcomes, which can also be extended to infant care. Firstly, there are health conscious women who actively seek prenatal and infant care who are more likely stick closely to clinicians' advice and follow a healthy lifestyle regime. Therefore, similar to the previous analysis, the unobservable preference for healthy living will bias the coefficient on the healthcare variable upwards and create inconsistency – policies that make antenatal and neonatal clinic visits mandatory may not have as great an effect on cognitive outcomes as OLS would suggest. Conversely, those who have adverse health conditions may seek more care, which would underestimate the effect of the healthcare on cognitive development[3]. Also biasing the OLS estimates downwards would be those

[3] An attempt to proxy for the adverse health conditions for both the mother and the child was made by controlling with a dummy variable for if the child suffers from a long term health condition or not.

mothers with “confidence” in their good health status and the health status of their child, most likely by believing that the antenatal and infant healthcare isn’t needed, yet the children may still experience good outcomes (Garrido, 2009). In the interest of saving space, the tests for endogeneity[4] are not explicitly set out, rather the similarity or difference between the estimates of OLS and 2SLS can be studied in the table that contains the variables of interest for each model.

Two-Stage Least Squares Regression Model

First stage:

$$H_{ik} = \tau + Z_{ij} + \theta\mathbf{X}_i + v_i$$

Second stage:

$$S_{ij} = \alpha + \beta H_{ik} + \rho\mathbf{X}_i + u_i$$

It is worth noting that all the right hand side variables in the main structural equation are concerned with choices made by the mother/carer and household characteristics during the early-life of the child. Controlling for variables in later rounds may be misleading if they are highly correlated with these observed characteristics in round one of the survey. The vector of controls $\mathbf{X}_i$ includes the household wealth index to proxy for income[5]

The Instruments (Z_l)

IV (Z_{i1}): APP: Average Pharmaceutical Prices:

Constructed variable: an average of the two community prices for 4 pharmaceutical products: Oral rehydration salts, Paracetamol tablet, Amozycillin tablet, Mebendazole deworming tablets.

IV (Z_{i2}): MIDWIFE: **“**Is there a trained midwife available to members of name of community?”

IV (Zi_3): WANTCLD: “When you became pregnant with the index child did you want to become pregnant at that time?”

Outcomes were robust when this variable was added, and it was insignificant in these models for cognitive outcomes. This may be because it is a bad proxy for the unobservable, or that those with adverse health conditions are of that state because of their lack of healthcare.

[4] Formally testing for endogeneity is carried out by determining if statistically significant differences are present between the estimates for OLS and 2SLS.

[5] For simplicity, from hereafter ‘income’ and ‘wealth index’ will be used interchangeably.

At the centre of the identifying assumptions is the main restriction that these variables are not correlated with the error term in the structural equation. This exclusion restriction is untestable; a review of basic economic relationships indicates whether the instruments are likely to have an orthogonal relationship with the unobservables in the error term or not. Garrido (2009) notes that the majority of studies have employed instrumental variables techniques, whereby the instruments are “the availability of medical services in the mother’s area of residence” (ibid), which are equivalent in this context to MIDWIFE and AVP. The possibility that mothers could migrate based on their preferences for more readily accessible healthcare in terms of either prices or ‘availability of a midwife’ may cause these variables to be correlated with these unobservable preferences.

In an attempt to build upon the status quo in the literature, and avoid the potential unwanted correlation of the availability of healthcare services, I make use of the WANTCLD variable in the Young Lives data set. This variable is positively and significantly correlated with both variables concerning iron supplementation. The hypothesized relationship is based on the fact that agents will be less willing to spend time and money on unwanted children during pregnancies. Furthermore, this variable is less likely to be correlated with the unobserved variables, and hence is more likely to suffice the exclusion restriction, because failures of contraception mean that unwanted pregnancies occur for women across all spectrums of characteristics. However, it is worth noting that perhaps those who are more concerned with their healthcare (as in Garrido, 2009), and those who are genetically more intelligent may experience a lower rate of unwanted pregnancies due to a greater uptake of advice from clinicians of the correct and most appropriate use of different forms of contraception. There are legitimate doubts concerning whether the exclusion restriction holds for these instruments, which must be kept in mind when interpreting the results in the latter section.

The relevance of the instruments was tested by running an OLS regression, and ensuring that the null hypothesis that the coefficient was equal to zero was rejected at a five percent significance level (by observing the p-value). As cluster-robust standard errors were employed in the 2SLS estimation, they were also used when determining the relevance of instruments.

Table 2

Endogenous variable	***Instrument***
INJECT	*APP*
IRONTABS	*WANTCLD*
IRON3MTH	*WANTCLD*
FOODNUT	*APP*
MEASLES	*MIDWIFE*

After testing instruments for all seven endogenous variables, five demonstrated relevance. However, no exogenous variables were found to be significantly correlated to the BCG and Polio vaccinations and also satisfy the exclusion restriction.

***Results I** – Table 3*

VARIABLE OF INTEREST	Highest School Grade	PPVT Score Age 5	Cognitive Score Age 5	PPVT Score Age 8	Math Score Age 8	Reading Score Age 8	PPVT Score Age 12	Math Score Age 12	English Score Age 12	Language Score Age 12
Coefficients for prenatal healthcare variables of interest (reported for OLS and 2SLS estimation Procedures										
INJECT(OLS)	**0.157***	**4.712*****	**-0.454****	**7.962*****	**1.459*****	**0.526***	**1.246****	**0.707**	**0.467***	**0.552***
	(0.0811)	(1.537)	(0.173)	(2.028)	(0.465)	(0.269)	(0.549)	(0.447)	(0.253)	(0.321)
R^2	0.026	0.152	0.085	0.106	0.128	0.039	0.092	0.156	0.255	0.094
INJECT (IV)	**-2.391*****	**260.6****	**9.297****	**50.81**	**-13.42**	**-2.039**	**3.175**	**-1.578**	**5.614*****	**7.449***
	(0.905)	(102.4)	(4.188)	(34.91)	(19.37)	(4.675)	(6.559)	(6.783)	(2.008)	(3.832)
IRONTABS (OLS)	**0.140***	**2.884****	**-0.389****	**8.119*****	**1.713*****	**0.572****	**0.950***	**0.940****	**0.395***	**0.654****
	(0.0772)	(1.359)	(0.164)	(1.899)	(0.446)	(0.267)	(0.504)	(0.417)	(0.224)	(0.282)
R^2	0.026	0.149	0.084	0.107	0.131	0.040	0.091	0.158	0.255	0.096
IRONTABS (IV)	**3.310**	**29.50**	**8.535**	**67.44**	**28.99**	**8.242**	**24.89**	**22.18**	**19.32**	**9.410**
	(2.757)	(35.14)	(9.289)	(66.00)	(25.94)	(6.740)	(23.82)	(24.71)	(18.99)	(10.68)
IRON3MTH(OLS)	**0.163****	**0.127**	**-0.263**	**7.316*****	**1.748*****	**0.667*****	**1.114****	**0.915****	**0.420****	**0.647****
	(0.0732)	(1.069)	(0.163)	(1.741)	(0.423)	(0.239)	(0.473)	(0.364)	(0.200)	(0.259)
R^2	0.028	0.146	0.083	0.108	0.135	0.043	0.093	0.158	0.255	0.097
IRON3MTH (IV)	**2.043**	**13.03**	**3.744**	**29.22**	**9.676*****	**3.583****	**10.92**	**9.771**	**8.701****	**3.113**
	(1.428)	(9.664)	(2.347)	(18.54)	(3.677)	(1.756)	(8.552)	(7.461)	(3.961)	(2.929)
Coefficients for infant healthcare variables of interest (reported for OLS and 2SLS estimation Procedures										
FOODNUT (OLS)	**-0.0885**	**3.870****	**-0.0214**	**2.987**	**0.773***	**0.585****	**0.735**	**1.051*****	**0.264**	**0.869*****
	(0.200)	(1.710)	(0.167)	(1.925)	(0.417)	(0.235)	(0.524)	(0.375)	(0.202)	(0.287)
R^2	0.092	0.156	0.084	0.102	0.129	0.044	0.091	0.164	0.261	0.103
FOODNUT (IV)	**-0.647*****	**60.45*****	**2.013*****	**11.09**	**-3.232**	**-0.651**	**0.311**	**-0.268**	**1.547****	**2.154***
	(0.172)	(11.84)	(0.604)	(7.963)	(3.512)	(0.963)	(1.853)	(1.935)	(0.612)	(1.206)
BCG (OLS)	**0.0615**	**5.235*****	**0.265**	**-1.577**	**0.290**	**0.168**	**1.408****	**1.251****	**1.202*****	**1.074*****
	(0.129)	(1.578)	(0.229)	(2.447)	(0.522)	(0.312)	(0.584)	(0.598)	(0.352)	(0.408)
R^2	0.023	0.152	0.082	0.099	0.124	0.037	0.089	0.158	0.260	0.097
POLIO (OLS	**0.221**	**3.335**	**0.488**	**-1.087**	**0.167**	**0.0354**	**0.694**	**1.455***	**0.417**	**0.769**
	(0.179)	(2.245)	(0.320)	(3.103)	(0.715)	(0.427)	(0.768)	(0.806)	(0.386)	(0.529)
R^2	0.025	0.149	0.083	0.099	0.124	0.037	0.087	0.158	0.256	0.095
MEASLES	**0.247*****	**4.720*****	**0.580*****	**4.714*****	**0.886****	**0.783*****	**2.084*****	**0.402**	**0.428***	**0.475****
	(0.0664)	(1.231)	(0.161)	(1.531)	(0.348)	(0.178)	(0.493)	(0.341)	(0.246)	(0.229)
R^2	0.035	0.148	0.088	0.105	0.132	0.049	0.097	0.161	0.258	0.098
MEASLES (IV)	**-0.559**	**124.3*****	**10.10****	**31.60**	**-2.508**	**2.490**	**5.016**	**-3.601**	**-1.456**	**1.020**
	(0.942)	(48.08)	(4.439)	(36.09)	(10.76)	(5.246)	(9.460)	(7.207)	(3.722)	(4.332)

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

The OLS estimations give consistently significant coefficients and mostly positive effects on the cognitive development outcomes – in line with the literature. Turning to the results from the instrumental variable technique to the statistically significant healthcare variables, there appears to be less healthcare variables that 'matter' compared to OLS. Yet it is still clear that they are important for cognitive outcomes; there is at least one healthcare variable that has a significant and positive effect on each of the dependent variables, apart from the PPVT score at ages 8 and 12, and the mathematics score at age 12. Considering, for example, the effect of IRON3MTH on the mathematics scores for children age 8, there is a positive and significant effect of 9.98 'points'.

There are three results from the IV estimation that stand out as much larger than the majority. They all concerning the outcome variable PPVT score at age 5 and are coefficients of the magnitude of 260.6, 60.5 and 124.3 for INJECT, FOODNUT and MEASLES respectively. As the range of the PPVT score (age 5) is 119 in the sample, it is hard to believe that these infant and prenatal variables have such an impact on the test scores way above any suggestions seen in the literature. Therefore, this is most likely to be a case of weak instruments and possible correlation between the instruments and the error term. Even if $\mathrm{Corr}(Z_j, u)$ is only moderate through the potential relationships discussed above, if the instruments are weakly correlated with the endogenous variable, this can result in a large asymptotic bias of coefficient estimates. Taking MEASLES as an example, comparing the Kleibergen-Paap rk Wald F statistic (7.145), to the Stock-Yogo weak ID test critical values for 15% and 20% maximal IV size (in this case 6.66 and 8.96), (from Stock-Yogo, 2005), it cannot be rejected that the instruments are weak in the sense that they have a 15% maximal size distortion. This isn't particularly weak, and the bias is likely coming from the violation of the exclusion restriction.

Moreover, looking at the case for PPVT score age 5 on INJECT, using the Kleibergen-Paap rk LM statistic, the null for underidentification cannot be rejected in this case, therefore the excluded instrument isn't relevant here. Dropping missing values in order to compute the estimates from the regressions may be a reason why the assumption of relevance does not hold in this case - it had initially been tested on the full sample. Although the other coefficients look reasonable, these large distortions are a sign to take the estimates as an illustration that a positive relationship between early-life healthcare and cognitive outcomes is likely to exist, rather than taking notice of the magnitudes.

After attempting to account for endogenous selection effects, it might be more beneficial to consider OLS as the main indicator of the nature of the relationships between the seven healthcare variables and the ten cognitive outcomes. Wooldridge (2009) proposes a case for using control variables that proxy for the unobserved characteristics that enter the error term. One argument against using the wealth index of the household and the highest grade reached by the mother as a proxy for genetic intelligence, is that in developing countries, stages of education reached aren't as strongly correlated with inherent ability for women. Again, this comes back to the gender discrimination story. Although taking this into account, the wealth index of a household will also include a measure of father's income, which is more likely to be correlated with his intelligence due to more employment opportunities for male applicants. Father's level of intelligence will both influence the decisions made by the mother and also have the heritability of intelligence implications as explained previously. If the wealth index does proxy for the genetic intelligence in the error term, then under certain assumptions the estimator of the coefficient of interest will be consistent.

Robustness tests aren't particularly crucial in this case as there are many well documented studies that have produced similar outcomes. For example, Bharadwaj et al. (2012), link later life educational achievement back to early childhood health interventions using a regression discontinuity framework. This postulates that the relationship holds throughout many different modelling methods. Furthermore, the low R^2 values reported for the OLS regressions aren't too much of a cause for concern as "R^2 values tend to be relatively small with microeconomic, and cross-sectional data, because variations in individual behaviour are difficult to completely account for and explain" (Carter-Hill et al., 2008).

Econometric Analysis: Gendered Patterns in Healthcare

Sampling According to Ultrasounds

Although the Young Lives data doesn't include a variable for receipt of ultrasound (as used in Lhila and Simon, 2008), and although it is illegal for a clinician to disclose the sex of a child to the parents according to the Pre-natal Diagnostic Techniques (Regulation and Prevention of Misuse) Act 1994, I adjust the sample in order to study a cohort for which is it possible they found out the sex of the fetus. The prevalence of sex selective abortions outlined by the literature gives a clear indication that that parents in India are unlawfully finding out the sex of their unborn child. I extend this assumption so that it is only clinicians at the registered antenatal clinics that have the equipment and expertise to illegally disclose the gender of the child, hence there are no 'black-market' or 'backstreet' clinics. Firstly, I drop those agents from the sample who did not receive any antenatal care at all. Then, using the variable for 'number of antenatal visits' and 'month of pregnancy of first visit', I am able to eliminate the agents from the sample who only made one visit before month five of pregnancy[6]. This cut-off point was chosen as this is the point during gestation when the sex of the child can be revealed through an ultrasound (Lhila and Simon, 2008; NHS, 2016), and although other gender determining procedures are available that could reveal the information earlier, they are more costly, and unlikely to be of widespread use in Andhra Pradesh and Telangana.

Table 4

	Ultrasound possible (n = 1730).	***Ultrasound not possible (n = 281).***
SEX	Percent.	Percent.
FEMALE	46.88	42.35
MALE	53.12	57.65

Where the ultrasound isn't possible, it is expected that the sex ratio would be statistically "similar" to the natural sex ratio at birth, as the parents wouldn't have known the sex in order to make a decision on a sex selective abortion. However, sample selection issue is likely to have come into play, as those who didn't go to an antenatal clinic, or only managed to visit once, before the 20-week mark, are more likely to be within low income cohort. Therefore, constrained household budgets and the desire for sufficient income to be brought into the house will likely instigate the strongest preferences for male offspring and thus the practice of female infanticide. With a larger sample size, it may have been appropriate to constrain the sample for the infant variables to the 'ultrasound not possible' cohort to eradicate the possibility of sex selective abortion. In this essay I shall use the ultrasound analysis only for the prenatal healthcare variables, by cutting down the sample to 'ultrasound possible' and allowing gender preferences to be acted upon during pregnancy.

[6] Although it is possible that some agents may have made multiple visits before this 'cut-off', they cannot be identified due to the nature of the available variables.

The Data

Table 5

Summary statistics: the dependent variables II				
Variable (H_{ij})	Yes *Boys* (%)	No *Boys* (%)	Yes *Girls* (%)	No *Girls* (%)
INJECT (H_{i1})	85.1	14.9	87.2	12.8
IRONTABS (H_{i2})	82.5	17.5	84.6	15.4
IRON3MTH (H_{i3})	76.5	23.5	78.4	21.6
FOODNUT (H_{i4})	68.3	31.7	66.6	33.4
BCG (H_{i5})	92.3	7.7	92.6	7.4
POLIO (H_{i6})	95.9	4.1	94.8	5.2
MEASLES (H_{i7})	72.2	27.8	73.2	26.8

For full sample.

Independent variables

In the analysis of the economic causes and consequences of a gender bias in this healthcare setting, WANTCLD is also a variable of interest. In a country which displays an obvious male preference paired with anti sex selective abortion laws, it would be expected that there would be a negative correlation between WANTCLD and SEX. However, Spearman's test for the correlation of ordinal data was ran on between SEX and WANTCHLD, and consequently the null that the two variables are independent cannot be rejected at a conventional level of significance, even when the test is ran for the sample that is corrected for sex selective abortions through the methodology outlined below. If sex selective abortions are somehow reduced in India without any changing of preferences or the value of the inputs into the household utility function (i.e. expected wages for female agents), there will be an increase in unwanted children. This variable adds to the analysis of what could potentially occur in terms of the healthcare distribution across the genders if there was a reduction in sex selective abortions in India.

Similar to the first section of econometric analysis, the the vector of controls, $\boldsymbol{\Omega}_i$.include the wealth index to proxy for income, and the highest grade reached by the mother (or carer). Furthermore, a community level binary variable indicating whether a village health worker is available or not is included for the three prenatal outcome variables, and the variable that accounts for if a trained midwife is available is used in the regressions for the outcome variables during infancy.

The Model

To determine if a a gender gap in early-days healthcare exists, I implement a logistic regression model. Although often the probit model is preferred over the logit, due to the assumed standard normal distribution of the error term rather than the logistic distribution, however results are often very similar, and indeed they are in this context. So, the logit model is implemented to exploit the convenience of the related odds ratios for this evaluation. Here the binary outcome variable that indicates whether the particular healthcare type has been received or not is regressed onto the dummy for gender (coded as '1' for male and '0' for female), plus the second variable of interest indicating whether the mother wanted to be pregnant at the time (coded as '1' for 'wanted to be pregnant at the time' and '0' alternatively), and the vector of controls.[7]

$$\frac{\Pr(H_{ik}=1)}{1-\Pr(H_{ik}=1)} = \exp(\sigma + \gamma SEX_i + \mu WANTCLD_i + \mathbf{\Omega}_i)^8$$

Again, to account for the intra-cluster correlation, I cluster the standard errors at a community level, assuming that there is an adaption of community specific behavioural norms related to childcare. For example, there may be a within community spreading of knowledge concerning the importance prenatal and postnatal healthcare, or simply the notion that if close friends and family demonstrate certain behaviours during the pregnancy and early infancy of their children, this is likely to be mimicked. Furthermore, as the two control variables indicating the availability of a village health work or midwife are indexed by community, each community will receive an idiosyncratic type of care depending on the quality and particular expertise of these workers, if available. Indeed, comparing the sizes of the standard errors of a model with and without accounting for clusters implies that they are underestimated when using 'normal' standard errors.

[7] It would be possible to construct a simple additive random utility model (ARUM), incorporating the microeconomic relationships discussed in the literature in order to form the basis of this econometric analysis.

[8] $y_i = \ln\left(\frac{\Pr(H_{ik}=1)}{1-\Pr(H_{ik}=1)}\right)$, is the latent variable that is reported when the logit command is used in Stata.

Results II

Table 6

Coefficient on variables of interest							
Variables	Prenatal			Infant			
	INJECT	***IRONTABS***	***IRON3MTH***	***FOODNUT***	***BCG***	***POLIO***	***MEASLES***
SEX	0.893	1.066	1.045	0.899	0.99	1.511**	1.0108
	(0.305)	(0.232)	(0.182)	(0.953)	(0.176)	(0.302)	(0.114)
WANTCLD	4.042***	2.296***	2.233***	1.364	1.584*	1.07	1.2
	(1.252)	(0.671)	(0.522)	(0.268)	(0.378)	(0.370)	(0.242)

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

The results from the data analysis are presented in the form of odds ratios ($\frac{\Pr(H_{ik}=1)}{1-\Pr(H_{ik}=1)}$), as these are relatively easier to interpret than the log-odds form. For a male, the odds of receiving a polio jab are 1.5 times larger than the odds for a female. During a pregnancy that was wanted, the odds of a mother receiving two or more tetanus injections are 4.04 times larger than if the pregnancy was unwanted. Similarly, the odds of the mother taking an iron supplement for three months of the pregnancy are 2.3 times higher. As noted, this relationship comes into the gender story indirectly, and suggests that if there is a 'forced' decrease in sex selective abortions, i.e. stricter laws, contingency policies will have to be implemented to ensure no negative treatment of unwanted children, who are more likely to be girls than boys.

Sex-Selective Abortions and Female Infanticide

So, without accounting for polio, the above results look promising in terms of gender equality in early-life healthcare, in terms of the direct SEX variable. However, the assumption that the error term is independent of the dependent variables is crucial to this econometric analysis, and the prevalence of sex selective abortions and female infanticide in India creates a sample selection bias whereby there is a certain threshold of 'wantedness' of a female child that has been attained for them to be present in the Young Lives cohort. It is assumed that at some point the costs of aborting (or carrying out female infanticide[9]) will outweigh the costs of raising a female child, that include the opportunity cost of expected wages forgone by her male equivalent, and the direct costs imposed by the dowry system. It is beneficial to estimate the effect of the sex of a child for a sample that will be representative of a population with an

[9] from hereafter in this essay I will focus on the issue of sex selective abortions, but female infanticide can easily be added to the analysis.

inherent male preference (that we know is the norm in India), but that hasn't carried out sex selective abortions. Constructing estimates of the effect of gender for this sample will go some way in illustrating the potential indirect effects on female health from policies that achieve the ultimately desirable goal of sex-selective abortion reduction.

There are biological reasons for a natural sex ratio at birth that is slightly skewed towards males – it lies at around 105 males for every 100 females. (WHO, SEARO, 2016). Unfortunately, it is a well-known fact that in South and South-East Asian countries, the entrenched preference for sons has resulted in widespread sex-selective abortions and female infanticide. A recently published estimate in *The Lancet* of the abortion rate in South and Central Asia (per 1,000 women, 15-44 years old) was 32% between 2000-04 (Sedgh et al., 2016)[10], which covers the year of the Young Lives survey in 2002. A 1992 study of female infanticide in South India finds that it is practiced in half of the villages studied, and affects around 10 percent of new-born girls (George et al., 1992). Female infanticide and sex-selective abortion figures are likely to be underestimated due to the laws against this behaviour in India. Furthermore, these policies and laws for prevention do not seem to be statistically significant in changing behaviour, as Sedgh et al. also reported that after grouping countries "according to the grounds under which abortion was legal, we did not find evidence that abortion rates for 2010–14 were associated with the legal status of abortion".

Table 7

Natural sex ratio

SEX	Percent.
FEMALE	48.78
MALE	51.22

To deal with this selection problem, Barcellos et al. (2012) restrict their sample to families with a child between the age of 0 to 15 months, hence still young enough that the mother hasn't been able to respond to the sex of the child by having other children. They argue that "a correlation will develop over time between the youngest child's gender and the family characteristics, because families with a newborn daughter are less likely to stop having children" (Barcellos et al., 2012). As the Young Lives sample is already constrained to children who are around the age of one year, following a similar line of

Table 8

Full YL sample (N = 2,011).

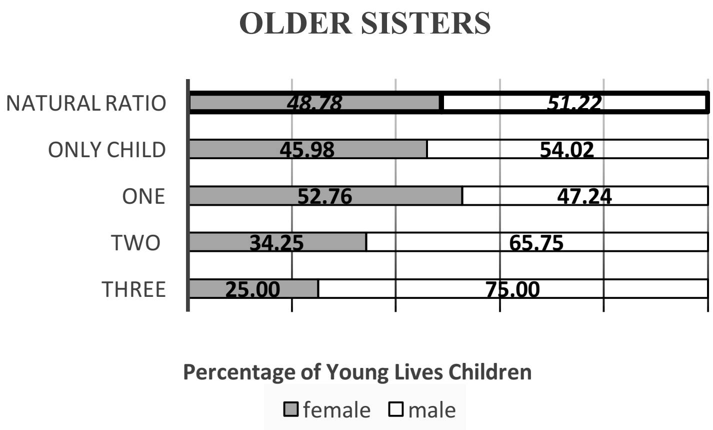
SEX	Percent.
FEMALE	46.25
MALE	53.75

[10] There are particular drawbacks for these estimates in the case of India as the quantity and precision of data is lower for developing countries.

reasoning, I run binomial tests (as they can be used on both large and small samples) on the gender ratio of samples that contain children with no siblings, children who have one older sister, with two older sisters, and finally for a child with three older sisters. Under the null hypothesis, (without sex selective abortions), the probability of "success", i.e. the binary variable being equal to one should be, $P = 0.5122$. Then for each sample, the null is either rejected or failed to be rejected[11] and we can measure whether the population is or isn't statistically different from the natural sex ratio at conventional significance levels.

The samples with only one child or with one older sister do not differ significantly from the natural ratio. Then for the sample with two or three older sisters, we reject the null that equates to the natural ratio. To obtain a sample with a homogenous household composition, and to eliminate the discussion of arguments based on allocation amongst siblings depending on their birth order, consequential analysis is carried out on the sample that contains households with an 'only child'[12].

Fig. 1



Additional to this, in order to uncover gender bias where it is expected be more prevalent, I cut the sample down to those with a wealth index value equal to the median or below[13] (see appendix ii for the gender ratios of the two samples obtained).

[11] using a two-sided test at a 5 percent level of significance.
[12] N.B. these samples don't account for siblings who may have died.
[13] Median of the wealth index: 0.3888889.

Results III

Table 9

Coefficient on variables of interest							
	Prenatal (ultrasound possible)			Postnatal			
VARIABLES	***INJECT***	***IRONTABS***	***IRON3MTH***	***FOODNUT***	***BCG***	***POLIO***	***MEASLES***
SEX	0.155	1.346	1.906**	0.953	1.047	2.472*	1.335
	(0.582)	(0. 455)	(0. 568)	(0.197)	(0.376)	(1.179)	(0.294)
WANTCLD	3.831	2.140	2.244	1.635	1.334	-	0.707
	(2.475)	(1.186)	(1.014)	(0.560)	(0.722)		(0.260)

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

It is worth noting that although the control variables aren't displayed for space preserving intentions, when the sample is restricted to median income and below, 'WI' becomes insignificant in all seven of the models. This implies that income doesn't have a monotonic relationship with the probability of obtaining prenatal and infant healthcare, perhaps due to government provision. Also, WANTCLD is omitted from the POLIO as it predicts success perfectly. In this particular sample, the odds that a mother bearing a male fetus takes iron supplementation for at least three months is 1.9 times higher than if the child was a girl, at a significant level according to the individual Wald test. As in the full sample, gender is significant for the receipt of a polio vaccine. The odds of a male receiving the vaccine is 2.4 times that of a female infant. Really, the focus of this essay is on the marginal effect of gender, hence the predicted difference in the probability of the child (or pregnant mother) receiving the healthcare between male and female agents[14]. Rather than calculating the margins while holding the other variables 'at their means', the average marginal effects are preferred in this context, as mostly binary variables are used and so a 'mean' of these variables isn't representative of any agent that exists in reality.

[14] Margins here are calculated assuming the variable is continuous, but is a good approximation.

Table 10

The Average Marginal Effects							
	Prenatal (ultrasound possible)			Postnatal			
	INJECT	***IRONTABS***	***IRON3MTH***	***FOODNUT***	***BCG***	***POLIO***	***MEASLES***
SEX	0.00626	0.0209	0.0768**	-0.0105	0.00333	0.0330*	0.0573
	(0.0220)	(0.0237)	(0.0360)	(0.0445)	(0.0258)	(0.0186)	(0.0435)
n	324	428	428	509	510	467	510

Robust standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

The value of the log-likelihood function cannot be used for interpretation of the goodness-of-fit of logit models when a clustered maximum likelihood estimate approach is used. For the two models with statistically significant variables of interest, instead the goodness-of-fit can be assessed through analysis of the sensitivity and specificity of the models. Low specificity is a problem, because although the model correctly classified 96.15% of the observations, the specificity value of 0% implies that this model will fail to predict when the healthcare isn't obtained. A similar pattern is seen for the IRON3MTH regression. The direction of the coefficients models appeared to be robust when the control variables were removed, and others when others were added - such as a binary variable for a long-term health problem to account for potential selection into healthcare as proposed by Garrido (2009). Furthermore, I ran the equivalent models but with a logit regression for a robustness check, and it was found that the coefficients only changed by a minor amount. A further robustness check that could be implemented would be to compare a model with a nonparametric maximum likelihood estimator as this estimation doesn't require parameterised probability distributions of the errors.

Conclusions

This essay provides an overview of the economic causes and consequences of a disparity in the allocation of early-life health across the genders in the context of India. The key assumptions and flaws of instrumental variable estimation are highlighted, but a strong argument for the positive relationship can be demonstrated. For the determination of a gendered pattern of healthcare investment, a unique approach is taken in order to circumvent the selection problem posed by widespread practice of sex-selective abortions and female infanticide. The policy implications from this analysis are two-fold. Firstly, there is a case for intervening in the allocation of early-life healthcare, as the lower level received by female agents is one mechanism by which economic and gender inequality is exacerbated. An intervention at this “critical” time period is also immensely effective in terms of influencing permanent positive outcomes. The scientific literature emphasizes the malleability of cognitive development paths during this window, and the econometric literature reinforces the notion of the effect on long term outcomes through cognitive development scores and wages. Secondly, health outcomes that will have a lasting effect upon earning ability, wages and welfare may change with policies that influence the rate of sex-selective abortions and female infanticide. Without a simultaneous cultural shift towards gender equality, policies that reduce sex-selective abortions may exacerbate the artificially skewed ability levels between the sexes. A drawback my concern the generalizability of these findings as the cohort survey and sample reduction resulted in a low income, largely rural sample. Nevertheless, this essay can be used as a basis to construct several useful RCT frameworks to allow for more rigorous testing of the hypotheses.

Appendix

(i)

Variable name		***Description (corresponding survey question)***
Prenatal	***INJECT***	“Did you receive two or more tetanus injections during the antenatal visits?”
	IRONTABS	“Were you given iron folate tablets or syrup during the antenatal visits?”
	IRON3MTH	“Did you take iron folate tablets or syrup for at least 3 months?”
Infant	***BCG***	“Did the child receive a BCG vaccine against Tuberculosis?”
	FOODNUT	“Has the child been part of a food supplement programme?”
	MEASLES	“Did the child receive a measles vaccine?”
	POLIO	“Did the child receive a vaccination against polio?”

(ii)

Only child, ultrasound possible, equal to or below median wealth index (n = 460).		Only child, equal to or below median wealth index (n = 535).	
SEX	Percent.	SEX	Percent.
FEMALE	48.48	FEMALE	47.29
MALE	51.52	MALE	52.71

References

Almond, D., & Currie, J. (2011). Killing me softly: The fetal origins hypothesis. The journal of economic perspectives: a journal of the American Economic Association, 25(3), 153.

Barker, D. J. (1990). The fetal and infant origins of adult disease. BMJ: British Medical Journal, 301(6761), 1111, Chicago

Barcellos, S. H., Carvalho, L., & Lleras-Muney, A. (2012). Child gender and parental investments in India: Are boys and girls treated differently? (No. w17781). National Bureau of Economic Research.

Barlow, J. L., Mung'Ala-Odera, V., Gona, J., & Newton, C. R. J. C. (2001). Brain damage after neonatal tetanus in a rural Kenyan hospital. Tropical Medicine & International Health, 6(4), 305-308.

Bharadwaj, P., Løken, K. V., & Neilson, C. (2012). Early life health interventions and academic achievement.

Bloom, D. E., Canning, D., & Shenoy, E. S. (2012). The effect of vaccination on children's physical and cognitive development in the Philippines. Applied Economics, 44(21), 2777-2783.

Borooah, V. K. (2004). Gender bias among children in India in their diet and immunisation against disease. Social Science & Medicine, 58(9), 1719-1731.

Carter Hill, R., Griffiths, W. E., and Lim, G.C. (2008). Principles of econometrics. Third edition. Hoboken, NJ: Wiley.

Currie, J., & Hyson, R. (1999). Is the impact of health shocks cushioned by socioeconomic status? The case of low birthweight (No. w6999). National bureau of economic research.

de Maeyer E, Adiels-Tegman M 1985 The prevalence of anaemia in the world. World Health Stat Q 38:302–316. | PubMed | ChemPort |

de Ungria, M., Rao, R., Wobken, J. D., Luciana, M., Nelson, C. A., & Georgieff, M. K. (2000). Perinatal iron deficiency decreases cytochrome c oxidase (CytOx) activity in selected regions of neonatal rat brain. Pediatric research, 48(2), 169-176.

Dercon, S., & Singh, A. (2013). From nutrition to aspirations and self-efficacy: gender bias over time among children in four countries. World Development, 45, 31-50.

Eden, A. N. (2005). Iron deficiency and impaired cognition in toddlers. Pediatric Drugs, 7(6), 347-352.

Fikree, F. F., & Pasha, O. (2004). Role

Fogel, R. W. (2012). Explaining long-term trends in health and longevity. Cambridge University Press.

Freire, W. B., (1997), Strategies of the Pan American Health Organization/World Health Organization for the control of iron deficiency in Latin America. Nutr Rev 55:183–188.

Garrido, G. G. (2009). The Impact of adequate prenatal care in a developing country: Testing the WHO recommendations. University of California, Los Angeles.
Chicago

George, S., Abel, R., & Miller, B. D. (1992). Female infanticide in rural South India. Economic and political weekly, 1153-1156.

Glewwe, P. (2002) Schools and skills in developing countries: education policies and socioeconomic outcomes, Journal of Economic Literature, 40, 436–82.

Herrendorf, B., Rogerson, R., & Valentinyi, Á. (2013). Growth and structural transformation (No. w18996). National Bureau of Economic Research.
of gender in health disparity: the South Asian context. Bmj, 328(7443), 823-826.

Heckman, J. J. (2007). The economics, technology, and neuroscience of human capability formation. Proceedings of the national Academy of Sciences, 104(33), 13250-13255.

Horton, S., & Ross, J. (2003). The economics of iron deficiency. Food policy, 28(1), 51-75. Chicago

Jha, P., Kesler, M. A., Kumar, R., Ram, F., Ram, U., Aleksandrowicz, L., ... & Banthia, J. K. (2011). Trends in selective abortions of girls in India: analysis of nationally representative birth histories from 1990 to 2005 and census data from 1991 to 2011. The Lancet, 377(9781), 1921-1928.

Kraay, A. (2012). Instrumental variables regressions with uncertain exclusion restrictions: A Bayesian approach. Journal of Applied Econometrics, 27(1), 108-128.

Kumra, Neha (2008) An Assessment of the Young Lives Sampling Approach in Andhra Pradesh, India, Technical Note 2, Oxford: Young Lives

Lhila, A., & Simon, K. I. (2008). Prenatal health investment decisions: Does the child's sex matter?. Demography, 45(4), 885-905. Chicago

Lozoff B (2000) Perinatal iron deficiency and the developing brain. Pediatr Res 48: 137–139.

Madheswaran, S., & Khasnobis, B. G. (2007). Gender Discrimination in the Labour Market:

Evidence from the NSS. WIDER research project on “Gender wage Gap and its Impact on poverty: Evidence from India.

Magar, V. (2015). Gender, health and the Sustainable Development Goals. Bulletin of the World Health Organization 2015, 93(743).

National Health Service, (2016). Can I find out the sex of my baby?. http://www.nhs.uk/chq/pages/1642.aspx?categoryid=54&subcategoryid=128, (accessed on 08/05/2016).

Neisser, U., Boodoo, G., Bouchard Jr, T. J., Boykin, A. W., Brody, N., Ceci, S. J., ... & Pasricha, S. R., Black, J., Muthayya, S., Shet, A., Bhat, V., Nagaraj, S., ... & Shet, A. S. (2010). Determinants of anemia among young children in rural India. Pediatrics, 126(1), e140-e149.

Sedgh, G., Bearak, J., Singh, S., Bankole, A., Popinchalk, A., Ganatra, B., ... & Johnston, H. B. (2016). Abortion incidence between 1990 and 2014: global, regional, and subregional levels and trends. The Lancet.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg.

UN Sustainable Development Goals. (2016). (https://sustainabledevelopment.un.org/?menu=1300), accessed on 01/06/2016.

UNICEF, (2016). First 1,000 days last forever: Scaling up nutrition for a just world, (http://www.unicef.org/tajikistan/Op-Ed_in_support_of_UNICEF_global_nutrition_report_adopted_TJK_facts_ENG.pdf), accessed on 01/06/2016

Urbina, S. (1996). Intelligence: knowns and unknowns. American psychologist, 51(2), 77.

WHO/UNICEF/Joint Committee on Health Policy (1994). Strategic approach to operationalizing selected end-decade goals: reduction of iron deficiency anaemia. UNICEF-WHO Joint Committee on Health Policy editor. JCHP30/95/4.5 1–8. Geneva WHO.

Wooldridge, J. (2009). Introductory econometrics: A modern approach. 4th Ed. Nelson Education.