The effect of fertility decisions on excess female mortality in India
Author(s): Daniel Rosenblum
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ORIGINAL PAPER

The effect of fertility decisions on excess female mortality in India

Daniel Rosenblum

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Abstract In India, many parents follow son-preferring fertility-stopping rules. Stopping rules affect both the number of children and the sex composition of these children. Parents whose first child is male will stop having children sooner than parents whose first child is female. On average, parents of a first-born son will have fewer children and will have a higher proportion of sons compared to parents of a first-born daughter. An economic model in which sons bring economic benefits and daughters bring economic costs, shows the importance of sex composition on child outcomes: holding the number of siblings constant, boys are better off with sisters and girls are better off with brothers. Empirical evidence using the sex outcome of first births as a natural experiment shows that stopping rules can exacerbate discrimination, causing as much as a quarter of excess female child mortality. Another implication of the research is that the use of sex-selective abortion may lower female mortality, but raise male mortality.

Keywords Child mortality · Fertility · India · Sex composition

JEL Classification J13 · J16 · O12

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D. Rosenblum (✉)
Department of Economics, Dalhousie University, Halifax NS B3H 4R2, Canada
e-mail: Daniel.Rosenblum@dal.ca

D. Rosenblum
Centre for Global Health Research, Li Ka Shing Knowledge Institute,
St. Michael's Hospital, 30 Bond Street, Toronto,
ON M5B 1W8, Canada

1 Introduction

Child mortality in the least developed countries (LDCs) is high. The under-five mortality rate in LDCs is over 15 % compared to 0.6 % in industrialized countries.[1] Furthermore, in most of the countries of South Asia and in China, girls have significantly higher mortality rates than boys (Fuse and Crenshaw 2006). For example, Arnold et al. (1998) find that for children aged 1–4 years in India, girls have mortality rates 43 % higher than boys. Higher female mortality is of particular concern because males are biologically weaker than females. Thus, without any discrimination against girls, we would expect higher mortality rates among boys, as is seen in all developed countries. There are several papers that find discrimination in South Asia against girls in the provision of health resources, yet the reasons for this discrimination are not well understood.

This paper focuses on how economic incentives cause excess female mortality, and, in particular, how these incentives drive fertility decisions that exacerbate discrimination against girls. Parents with a strong preference for sons use two methods to affect the sex composition of their children: sex-selective abortion and son-preferring fertility-stopping rules (shortened to "stopping rules" in this paper). A stopping rule is the practice of continuing to have children until one has a desired number of sons. The pervasiveness of stopping rules in India has been well documented (Clark 2000; Arnold et al. 2002). Stopping rules create a distribution of households.[2] Parents with a high proportion of sons will tend to stop having children, while parents with a high proportion of daughters will tend to grow larger. The desire to have sons has the unintended consequence of creating households with many daughters. Thus, stopping rules cause the average girl to be in a household with more siblings than the average boy. Stopping rules also increase the expected proportion of girls in a girl's family. One may hypothesize that parents could be treating their children equally, and girls are only disadvantaged on average because they have more siblings than boys (Jensen 2003). However, I argue that these larger households with a high proportion of girls are where parents treat their children the most unequally.

Another way for parents to affect the sex composition of their children is through sex-selective abortion, and its use should reduce the number of children in a household and increase the proportion of boys. Thus, in a way, selective abortion counteracts the effects of stopping rules, reducing non-aborted daughters' number of siblings and the proportion of girls in the household. However, unlike stopping rules, selective abortion directly reduces

[1] http://www.unicef.org/statistics/index.html

[2] See Keyfitz (1968) pp. 379–384 for a brief exposition on the mathematics of stopping rules.

the number of female births in the population. So, although selective abortion increases the missing women problem, it may reduce excess female mortality.

The main contribution of the paper is a methodological one. I present a model in which household fertility, sex composition, discrimination, and child mortality are simultaneously determined by economic incentives. I argue that all of these considerations must be taken into account in an empirical analysis of family formation and child mortality. Having more siblings than boys, the *household size effect*, causes girls to live in households with fewer resources per child. A substantial contribution of the paper is deriving the second consequence of stopping rules, the *sex composition effect*, from an economic model of fertility decisions and the future costs and benefits of girls and boys. The sex composition effect occurs when an increase in the proportion of girls in a household causes an increase in discrimination against girls and in favor of boys. Furthermore, I make a contribution to the literature on the connection between fertility decisions and child outcomes by showing empirically that the sex composition effect can have a larger effect on child mortality than the household size effect.

Any empirical attempt to find the effect of fertility stopping rules on child mortality are complicated by the possibility of reverse causality. The empirical approach to testing the effects of stopping rules on child mortality has two steps. First, using a large Indian household survey, I show that the sex of the first-born child is random and, in particular, that parents are not likely to selectively abort their first pregnancy. This plausibly exogenous variable solves some of the endogeneity problem between child mortality and fertility. Second, a reduced form approach uses the sex outcome of the first pregnancy as a natural experiment. A household that has a first-born boy has fewer children and a higher proportion of boys than a household with a first-born girl. A first-born boy causes boys to have higher mortality rates while causing girls to have lower mortality rates. That the mortality rate of boys is actually higher when they have fewer siblings of which a higher proportion are male means that the sex composition effect is stronger than the household size effect for male mortality. Several robustness checks support the results.

I find that the outcome of the first birth can explain about a quarter of the child mortality gap between boys and girls. The results also indicate that one consequence of sex-selective abortion is a reduction in the child mortality gap by improving girl mortality and worsening boy mortality. Sub-sample estimates indicate that stopping rules have a larger impact on child mortality in rural households. Furthermore, if the father is literate while the mother is illiterate, stopping rules have a larger effect on male mortality compared to parents who are both literate or both illiterate. In addition, evidence is provided that the sex outcome of the first-birth affects vaccinations of higher order births, supporting the hypothesis that fertility-stopping rules exacerbate parental discrimination in the provision of health resources.

2 Background

Demographers have known for a long time that India has a relatively low proportion of women. Visaria (1969) performed a detailed analysis of data available up to the Indian Census of 1961 and concluded that the low number of women can be explained by differences in child mortality rather than differences in sex ratios at birth or other possible explanations. Sen (1990) was the first economist to articulate the plight of "missing women," estimating that 100 million more women would have been alive if given the same health and nutritional resources as males. Refinements by Coale (1991) and Klasen (1994) provide smaller but still large estimates of the number of missing women. Recent estimates show that half a million pregnancies end in sex-selective abortions annually in India (Jha et al. 2006, 2011; Bhalotra and Cochrane 2010). However, Anderson and Ray (2010) look into the causes of missing women and find, like Visaria, that most of India's missing women are due to excess female mortality rather than selective abortion or infanticide.

Scrimshaw (1978) argues that parents may be purposefully causing infant mortality in order to regulate family size. Das Gupta (1987) and Muhuri and Preston (1991) follow up on that idea by examining the effects of sibling sex composition on child mortality in India and Bangladesh, respectively. They both find that girls appear to have lower mortality rates if they have brothers, and boys appear to have lower mortality rates if they have sisters. Pande (2003) finds that boys who have older sisters and girls who have older brothers are more likely to be immunized and avoid stunting, although she attributes this to a desire for gender balance within the household. A problem with these studies is that they do not have an economic model to explain their findings, they do not jointly take into account number of siblings and sex composition, and they do not have an identification strategy that allows causal estimates of sex composition on child mortality.

Several studies have documented the relatively poor treatment of girls in South Asia (Chen et al. 1981; Basu 1989; Hazarika 2000; Asfaw et al. 2007). However, there has been less attention given to the economic incentives that cause this discrimination. In India, sons and daughters have opposite future income effects on their parents, and these differences are likely to cause differences in childhood health investment. Aside from any labor income children accrue, sons acquire dowries when they marry, while parents must pay dowries and wedding costs to get their daughters married. These dowries can be large. Anderson (2003) suggests that 93–94 % of marriages in India include a dowry payment, and that these payments can amount to as much as six times a household's annual income. Furthermore, the prevalence of the joint household means that having a son creates a future expectation of more household workers, namely the son, his future wife, and their children. A daughter on the other hand leaves with her dowry and labor supply and can no longer be expected to contribute to her parents' household. Even if daughters could help their parents in their old age, women have lower income prospects than men. Thus, sons provide income security in old age, while daughters do not. Rosenzweig and Schultz (1982) argue that gender discrimination in India could be caused by the relative income of males versus females. Qian (2008) finds evidence of the importance of labor income for sex differences in mortality in China. I contribute to the literature by exploring how economic incentives influence fertility decisions which in turn create more discrimination against girls.

3 Model of fertility decisions and child investment

Cigno (1998) develops a theoretical fertility model that explicitly endogenizes childhood survival. However, he does not distinguish between boys and girls. Rosenzweig and Schultz (1982) provide an economic model linking the future income of boys versus girls in India to childhood survival. My model takes these models one step further by both treating fertility decisions as endogenous and allowing boys and girls to have different future benefits and costs for parents. The model can also be thought of as an extension of Becker and Lewis (1973)'s quality/quantity trade-off in having children, with boys and girls treated separately.

The model is different than many others explaining fertility decisions in that it explicitly takes sex composition into account. Other models that look at son-preferring fertility-stopping rules either focus on sibling size (Jensen 2003) or on birth-order effects (Basu and Jong 2010). Garg and Morduch (1998) investigate the effects of sex composition on child health in Ghana. In Garg and Morduch (1998)'s model, if the number of children are held constant, then having a higher proportion of girls in the household is good for all children. In the model below, boys benefit from a high proportion of sisters, but girls are hurt by a high proportion of sisters. Both models assume credit constraints. The major difference between the two models is that in Garg and Morduch's model, investments in girls' health or education always increase future household income (if at lower marginal returns compared to boys). The model below examines the Indian context where investing in a daughter's health reduces future household income. These costs of investing more in daughters are what drive stopping-rule behavior and the exacerbation of discrimination against daughters when there are a high proportion of daughters in the household. The model makes some strict assumptions, such as diminishing utility from income, credit constraints, an inability to change the costs and benefits of surviving children through investment, and the lack of sex-selective abortion as a fertility option. However, these simplifications increase the tractability of the model and highlight the essential incentives that could be causing fertility-stopping rules and excess female mortality.

This section presents a two-period model of fertility and child mortality. In the first period, parents make fertility decisions conditional on previous birth outcomes and then decide how much health capital, e.g., food and medical care, to invest in each child. There is a fixed cost to having each child regardless of how much the parents invest, e.g., a reduction in mother's labor supply in having and caring for a baby. At the end of the first period, children die via a survival function, in which the greater the parental investment in child health, the fewer children die. For simplicity, boys and girls are assumed to have the same survival function.[3] In the second period, the children become adults. Parents suffer a fixed cost for each daughter and parents receive a fixed benefit for each son. Thus, parents lose income if they have more surviving daughters than sons. One can think of a girl's cost being her dowry at the time of marriage, while a son's benefit is his labor income as he remains in the joint household and possibly the labor supplied by his new wife and children as well as his dowry income. The timing of the model is illustrated below:

- Period 1.
  1. Fertility decisions
  2. Health investment in children
  3. Child mortality occurs.
- Period 2.
  1. Parents pay the cost of surviving daughters and collect the benefits of surviving sons.

The parents act as a unitary utility maximizer.[4] Parents first make the decision to have children, where they either continue to have a child or stop fertility altogether, conditional on previous fertility outcomes. After fertility has stopped, parents invest in these children. Parents make their fertility decisions based on how their investments and, hence, expected lifetime utility, are expected to change if they have an additional child. Parents care about their own consumption in each period, c_j $(j = 1, 2)$. For simplicity, I assume that given N children, a continuous proportion π of them are boys, and $1 - \pi$ are girls, where $0 \le \pi \le 1$. Parents also care about the number of children who survive. They can increase the number of children who survive by investing in child health. $p(k_i)$ is the proportion of children of sex i surviving, which is a positive, strictly concave function of the average health capital invested in children of sex i, k_i, and $0 \le p(k_i) \le 1$. For simplicity, parents are assumed to know the exact proportion of children who survive given the health investment.[5] Thus, if parents invest k_B in their boys, then $p(k_B)\pi N$ boys will survive

[3]This assumption does not have an effect on the comparative statics of the model.

[4]See Eswaran (2002) for a model of fertility and mortality that includes intra-household bargaining.

[5]I follow along the lines of Rosenzweig and Schultz (1982). I avoid the complexity of probability distributions that are in Cigno (1998) and discrete children with binomial survival distributions as in Sah (1991). Note that the analytic results could change if expected utility and probability distributions of child survival are used, depending upon the choice of utility function, distribution, and risk aversion parameters.

to adulthood. Parents with N children, and who have decided to have no more children, have the following lifetime utility function:

$$U_T = U_1(c_1) + U_2(c_2) + U_S(p(k_B)\pi N + p(k_G)(1-\pi)N) \qquad (1)$$

The parents' lifetime utility (U_T) is the sum of their utility from consumption in the two periods, $U_1(c_1)$ and $U_2(c_2)$, and the utility of having their children survive, $U_S(\cdot)$. $U_1(c_1)$ and $U_2(c_2)$ are assumed to be positive and strictly concave with respect to consumption. $U_S(\cdot)$ is assumed to be positive and concave with respect to the number of surviving children. I assume that parents care about the survival of each child equally and, in the absence of their desire to spend on themselves, would equally allocate all their resources to their children. This assumption about survival utility highlights the tension in parents' allocation decisions: they want their children to survive, but they also want to consume resources for themselves. It may be the case that, in reality, parents care more intrinsically about a son surviving than a daughter or vice versa, and this is what drives discrimination. However, the model shows that discrimination will follow from economic incentives, even without different intrinsic preferences over child survival by sex.[6]

Parents have budget constraints in each period. In the first and second periods, parents receive exogenous incomes of Y_1 and Y_2 respectively. There is a fixed cost of F per child in the first period. This fixed cost is part of the household size effect: the more children there are, the less resources there are. The other aspect of the household size effect is also built into the model via the fixed income of parents: the more children there are, the less resources there are per child. In the second period, if children survive, parents must pay for daughters, but benefit from sons. For simplicity, the future cost of each surviving daughter and benefit of each surviving son is fixed at a positive number D. That is, it is assumed that D is unaffected by early childhood health investments. Households cannot save, borrow, or accumulate assets. This assumption about credit and saving constraints is crucial to Proposition

[6]By "intrinsic" preferences for child survival, I mean anything outside of parents' costs and benefits included in the D variable, which could include any economic costs and benefits of children. If parents do care intrinsically more about boys than girls (for cultural or social reasons), this strengthens the predictions of the model. The reason for the model's simplification is that economic incentives are sufficient to explain discrimination even if there are non-economic incentives for discrimination as well. One could go further and argue that the unfair economic incentives only exist because of social incentives, and the author concedes that this may be the case. Yet, a number of parents who find these social incentives unjust and do in fact care equally about their sons and daughters in a non-economic sense, may discriminate because of the economic incentives propagated by the social preferences of others.

1 below and is further discussed in Appendix B.[7] A household with N children has the following constraints for each period:

Period 1 budget constraint: $c_1 + NF + \pi N k_B + (1 - \pi) N k_G \leq Y_1$
Period 2 budget constraint: $c_2 \leq Y_2 + \pi N p(k_B) D - (1 - \pi) N p(k_G) D$

In the first period, parents spend their income on themselves, the fixed costs of having N children, and any investments they wish to make in their children. In the second period, parents consume whatever is left over of their income net of the costs of their surviving children. Parents make all their decisions in the first period, i.e., how many children to have and how much to invest in each child. Parents will want to keep their daughters alive if the survival utility outweighs the consumption utility cost. The results below assume an interior solution (in particular that parents invest a positive amount in their daughters).

From the model, the following three propositions hold (proofs given in Appendix A). Propositions 1 and 2 are the theoretical explanations for the sex composition effect: sons are better off with a higher proportion of sisters, and daughters are better off with a higher proportion of brothers. Proposition 3 provides an economic explanation for why parents follow stopping rules.

Proposition 1 *Assume fertility decisions have stopped (i.e., given a fixed N). If D is sufficiently large, then the greater the proportion of boys in a family, the less is invested in each boy:* $\frac{\partial k_B}{\partial \pi} < 0$.

The intuition for this proposition can be thought of in two ways. As the proportion of daughters rises, parents face a larger future cost from their daughters and a smaller future benefit from sons, and so, in order to help to reduce the future burden, they will want to ensure that their sons survive. Thus, having a higher proportion of sisters helps sons. From another perspective, a marginal increase in the proportion of sons means that parents have a larger future income. Parents will want to smooth this future income by transferring it to the present. Since parents are assumed not to be able to borrow against their sons' future incomes, they can only smooth their consumption between the two periods by reducing their expenditure on sons in childhood while increasing spending on their own consumption. Thus, having a higher proportion of boys hurts sons.

Proposition 2 *Assume fertility decisions have stopped. If D is sufficiently large, then the greater proportion of boys in a family, the more is invested in each girl:* $\frac{\partial k_G}{\partial \pi} > 0$

Proposition 2 follows from the income gains from a marginal increase in the proportion of boys, which allow parents to spend more on girls. Imagine

[7] As shown in Appendix B, if there are perfect credit markets, I predict the opposite of Proposition 1. However, given empirical evidence in India, it is likely that many households are, in fact, credit-constrained.

a girl with many brothers. The future costs of that girl are ameliorated by the presence of brothers, and thus parents can better afford to keep the girl alive. Or from the opposite perspective, the higher the proportion of daughters in the household, the more costly it is for parents to keep those daughters alive, and hence, they invest less in all of them. Thus, having a high proportion of boys is good for daughters.

Proposition 3 *Assume that there is a 50 % probability of having a boy or girl. Assume household 1 (HH1) has relatively more boys and household 2 (HH2) has relatively more girls, (i.e.,* $\pi_{HH1} > \pi_{HH2}$*), and both households have N total children. If D is sufficiently large, then parents in HH2 have a larger expected utility gain from a marginal increase in N than parents in HH1:* $\frac{\partial EU_{T,HH1}}{\partial N} < \frac{\partial EU_{T,HH2}}{\partial N}$*. That is, parents with relatively more girls have a stronger incentive to continue having children.*[8]

Proposition 3 follows intuitively from Propositions 1 and 2. A household with a high proportion of sons, compared to a household with a low proportion of sons, which then has an additional son, will invest less in each son (from Proposition 1). The high-son-proportioned household will thus expect smaller future gains from an extra son, since that son is more likely to die. The household with a high proportion of sons, compared to the household with a lower proportion of sons, which then has an additional daughter, will invest more in each daughter (from Proposition 2). The high-son-proportioned household will expect higher future costs from an extra daughter, since that daughter is more likely to live. Thus, the expected gain from more sons is smaller, and the expected loss from more daughters is larger in the high-son-proportioned household, giving it a smaller incentive to have an extra child on net compared to a low-son-proportioned household.

As the parents have children, those with girls are pushed to have more children. The resulting distribution creates a subset of households that are particularly disadvantageous to girls: girls are in larger households than boys on average, which hurts girls, and they are in households with a high proportion of girls, which is worse than if they had the same number of siblings with a higher proportion of boys.

[8] In the case of a discrete, rather than continuous, change in N, the expected future cost of an additional daughter depends on two competing factors. The first is the sex composition effect, which increases the mortality rate of all daughters if an extra daughter is added to the household. This effect is stronger in HH2 compared to HH1, and, thus, HH2 has a lower expected future cost (in terms of income) from an extra daughter. However, parents with a high proportion of daughters (HH2) are relatively poor compared to parents with the same number of children, but a lower proportion of daughters (HH1). Thus, if parents are sufficiently risk-averse, then the expected future income loss for HH2, although smaller than the expected future income loss for HH1, creates a larger loss in expected future utility for HH2 compared to HH1. That parents in India, in fact, follow fertility-stopping rules indicates that parents in general are not so risk-averse that they are unwilling to risk having an additional daughter.

Although selective abortion is not explicitly a part of the above model, the more daughters that parents have, the larger the future economic burden. Thus, a household with net future losses (with many girls) would gain more from selective abortion than a household with net future gains (with many boys). It is a key assumption for the empirical section that selective abortion occurs mostly in higher order births in India, so it is reassuring that the theoretical model supports this assumption.

4 Empirical strategy

This section describes a method to empirically test the household size effect and the sex composition effect. Ideally, if there was no endogeneity problem, it would be possible to simply regress boy and girl mortality on the number of children and their sex composition. However, higher child mortality increases the number of children parents want, which could also influence the sex composition of children. In particular, a change in a fertility-stopping rule will affect the number of children born and the sex composition of children. If families are more or less likely to selectively abort a pregnancy depending on the expected survival rates of their children, this will also change the number and sex composition of children.

Jensen (2003) and Angrist and Evans (1998) use the outcome of the first or first two pregnancies as an instrument for the number of children. Jensen (2003) follows a similar strategy to the one followed in this paper and uses the fact that parents' preference for sons in India will cause parents with a first-born son to have fewer children than parents with a first-born daughter. Angrist and Evans (1998) look at American data and use parents' preference for a sex-balanced family to predict more children if the first two births are of the same sex. However, Rosenzweig and Wolpin (2000) point out that the sex composition of children can affect the outcomes of interest, and, thus, the instrument is not necessarily valid. In particular, any household size effect may be conflated with the sex composition effect.[9]

Thus, we cannot instrument for the two endogenous variables: number of children and their sex composition. However, we can estimate the reduced form effect of a first-born boy versus first-born girl on child mortality, which in itself provides a test of the effect of household size and sex composition on

[9]Twins as a first pregnancy is another exogenous outcome that affects the number of children born and the sex composition of these children. Yet, it cannot reliably be used as an extra instrument because twins are different from non-twins, in particular having lower birth weight on average. This means that, for example, a pair of boy twins are biologically weaker than two sons born separately (Rosenzweig and Zhang 2009). To simplify the empirical analysis, I exclude all households with first-born twins which make up approximately 0.5 % of all observations.

child mortality.[10] If parents are following stopping rules, a first-born daughter predicts more children on average than a first-born son. Even if households were not following a stopping rule and having N children of random sex, a household with a first-born girl will have a higher proportion of girls on average than a household with a first-born boy. Stopping rules, just like having a first-born daughter, cause some households to have more children and a higher proportion of girls. Thus, one can think of the sex outcome of a first birth as a proxy for measuring the effects of stopping rules on child mortality.

While for girls, having a first-born sister is detrimental both through the household size and sex composition effect (Proposition 2), they have opposing effects for boys (Proposition 1). That is, a first-born sister is bad for a boy because he will have more siblings. However, a first-born sister is beneficial for a boy because he will have a higher proportion of sisters. If we find that a first-born boy predicts higher male mortality relative to boys in a household with a first-born girl, this can only be because the sex composition effect outweighs the household size effect. Thus, although we cannot estimate the exact size of each of these effects, we can test whether the sex composition effect is stronger than the household size effect for boys. We can then make the following empirical predictions:

Prediction 1 *Girls in households with a first-born boy (which predicts fewer children and a higher proportion of boys) will benefit from both the household size and sex composition effects and have higher childhood investment. This will result in lower childhood mortality than girls in households with a first-born girl.*

Prediction 2 *Boys in households with a first-born boy may have either higher or lower childhood investment. Fewer children decrease mortality via the household size effect, while the higher proportion of boys increases mortality via the sex composition effect.*

In order to use the sex outcome of a first birth as a natural experiment, I follow three steps. First, I show that the sex outcome of a first birth is plausibly exogenous. Second, I show that, indeed, a first-born son strongly predicts the number of children born as well as a higher proportion of male children. Last, I estimate the reduced form effect of having a first-born son on male and female child mortality. The estimation equation is as follows:

$$Y_{ij} = \gamma FirstBornBoy_i + \beta_1 X_i + \beta_j State_j + e_{ij} \quad (2)$$

The outcomes of interest for household i in state j, Y_{ij}, are the number of children born, the proportion of children born male, the child mortality rate of

[10] Dahl and Moretti (2008) use a similar estimation technique in the USA and find that first-born girls are disadvantaged compared to first-born boys. For example, first-born girls' parents are more likely to be divorced. Interestingly, a first-born girl in the USA predicts higher fertility, although by only one-fiftieth as much as in India.

male children, and the child mortality rate of female children. $FirstBornBoy_i$ is a dummy variable which takes on the value of 1 if the first-born child in a household is male and 0 if female. X_i are household variables: mother's age and years of schooling, father's years of schooling,[11] religion, caste, and whether the household is in a rural or urban area. X_i are included to reduce potential bias in the estimates. I also include state-fixed effects ($State_j$) to account for state level differences in the outcomes of interest. Since a first-born boy benefits girls through the household size and sex composition effects, I predict $\gamma < 0$ for female child mortality. For male child mortality, $\gamma > 0$ if the sex composition effect is stronger than the household size effect, while $\gamma \leq 0$ otherwise.

I define child mortality as the percent of children who die between the ages of 1 and 60 months, multiplied by 100, conditional on surviving up to 1 month of age. The model yields predictions on average boy and average girl mortality instead of on specific birth orders, which explains why the empirical results focus on average mortality. Average mortality is a useful metric in that it allows us to ignore the number of children born, which is endogenous. Children who die before 1 month are dropped from the sample because most deaths at this age are from birth defects or other issues not within parents' control.[12] The estimates are robust to including these deaths in the specification (see Appendix D for estimations that include deaths in the first month) and to extending the time period to, for example, 0–120 months of age (estimations not shown). Sixty months is a cutoff used in most of the literature on child mortality because a high proportion of child deaths occur before age 5. I only provide estimates for households where the mother is aged 35 years and older, when she is likely to have completed her fertility.[13]

First-born children are more likely to die than later-born children (Hobcraft et al. 1985). Thus, it would not be surprising to find that if we include first-births, boy mortality is higher and girl mortality is lower among households with a first-born boy. Given this fact, the sample is restricted to children of birth order two and higher.

An alternative interpretation of the estimation equation is that if parents do not selectively abort their first pregnancy, the sex outcome of the first birth will tell us what would have happened to a household if it had used selective abortion for the first pregnancy. Ignoring the direct costs of selective abortion, if we ask what households with first-born girls would look like if they had selectively aborted the first-born girls, the answer is that, on average, they would look like families with first-born boys. Thus, the sex outcome of the first

[11] Illiterate individuals are coded as having no years of education, which is not necessarily true. The estimates are robust to simply including dummy variables for literate/illiterate instead of years of education.

[12] See, for example, Simmons et al. (1978, 1982), and Smucker et al. (1980).

[13] Only 12 % of women in the RCH II have a child at age 35 or older, and more than 70 % of women aged 35 years and older have been sterilized.

pregnancy can also be used as a test of the impact of sex-selective abortion on child mortality.

Although I show that selective abortion is unlikely for first pregnancies, it is useful to discuss its implications for the estimates. As shown by Bhalotra and Cochrane (2010), sex-selective abortion tends to happen more frequently among wealthier households, which have lower child mortality rates. Thus, if sex-selection is occurring amongst first-borns, this would bias the estimated effect of a first-born boy on child mortality downward.

5 Data

The 2002–2004 Reproductive and Child Health Survey (RCH II) is used to test the model empirically. The RCH II is a nationally representative survey of approximately 500,000 ever-married women aged 13–44 years (IIPS 2006). The survey was implemented by the Government of India via the International Institute for Population Sciences (IIPS), with the goal to better understanding the demand for family planning, contraceptive use and reproductive knowledge, early child health, and utilization of health facilities. The survey is designed to be representative at the district level, covering all 593 districts from the 2001 Indian Census. The survey selected 40 primary sampling units (PSUs) per district, with the probability of PSU selection weighted by population. The proportion of rural to urban PSUs is designed to be close to the actual rural/urban population ratio in the district. Urban areas are over-sampled in districts with particularly small urban populations. Approximately 1,000 households were sampled per district. The use of such a large dataset, as opposed to the smaller Indian National Family Health Surveys (NFHS), is critical for this research. First, it allows enough power to verify the sex ratio at birth for first-borns. Second, since only a small percentage of children die, it more precisely estimates effects on child mortality.

The survey in the RCH II includes questions similar to the NFHS such as demographic information (age, education, religion, caste), as well as questions about child and mother health. In particular, the survey asks about the mother's complete birth history, including the age of death of a child if the child is dead. It includes detailed questions about the mother's most recently born children (antenatal care, vaccinations), family planning usage, and parents' health knowledge. The survey does not ask about household assets, landholding, income, expenditure, or wealth.

6 Exogeneity of the sex outcome of the first birth

In order for the empirical approach to be valid, it must be shown that the sex outcome of a first birth can be treated as a natural experiment. As noted by, for example, Portner (2010), Bhalotra and Cochrane (2010), and Jha et al. (2011), the first pregnancy in India has a biologically normal male/female sex ratio

Table 1 RCH II male/female ratio at birth by birth order

Birth order	All ages	95 % CI	Born within 10 years of survey	95 % CI
1st	1.089	(1.083, 1.095)	1.066	(1.056, 1.076)
2nd	1.088	(1.081, 1.095)	1.091	(1.080, 1.102)
3rd	1.100	(1.091, 1.109)	1.094	(1.081, 1.107)
4th	1.091	(1.080, 1.102)	1.091	(1.075, 1.108)
5th	1.070	(1.052, 1.082)	1.073	(1.054, 1.094)

Sample weights used; no twins. Data source is RCH II

(i.e., in the range of 1.04–1.07 males per female),[14] while later births have a higher sex ratio, indicating the use of selective abortion. As Ebenstein (2010) points out, we also see the phenomenon of increasing sex ratios among higher birth orders in China, where the first birth has an approximately normal sex ratio (also see Das Gupta 2005).

We cannot treat later births as random because some households choose to have these children only if the fetus is male. If parents do selectively abort their first pregnancy, this will present a selection bias for the reduced form estimates in the paper. For example, if parents who selectively abort are those that are richer or better educated or have better access to health facilities, then we would expect that in families with first-born girls, girls are more likely to die for reasons completely outside of resource discrimination within a household.

Table 1 presents estimates of the sex ratio at birth by birth order using the RCH II. The sex ratio for first-borns among all women surveyed is 1.089, greater than what we would expect to occur naturally. This number is deceptive because older interviewed women potentially have recall bias about their birth history. Recall bias occurs when parents had a first-born daughter, but the daughter died during infancy and parents do not report the first-born daughter. Such recall bias has been reported in China (Smith 1994) and in India for the National Family Health Surveys (IIPS 1995). Another issue is survival bias because having a first-born girl increases the total number of children born, which in turn increases maternal mortality. Households where the mother is dead are excluded from the survey.[15] Recall and survival bias is reduced if we restrict the sample to more recent births. For children who were 0–10 years old at the time the survey was taken, the male/female ratio for first-borns falls to 1.066, in the range considered normal, while remaining high for higher birth orders.

Figure 1 illustrates changes in the sex ratio at birth over time in the RCH II. The male/female sex ratio is high in the 1980s but drops to normal levels for more recent births. Selective abortion did not become widely available in

[14]See Chahnazarian (1988) for a review of literature on the biologically normal sex ratio at birth and Parazzini et al. (1998) on global trends in the sex ratio at birth.

[15]Using back-of-the-envelope calculations, I find that 1.7 percentage points of first-born daughter households are missing from the survey due to recall and survival bias.

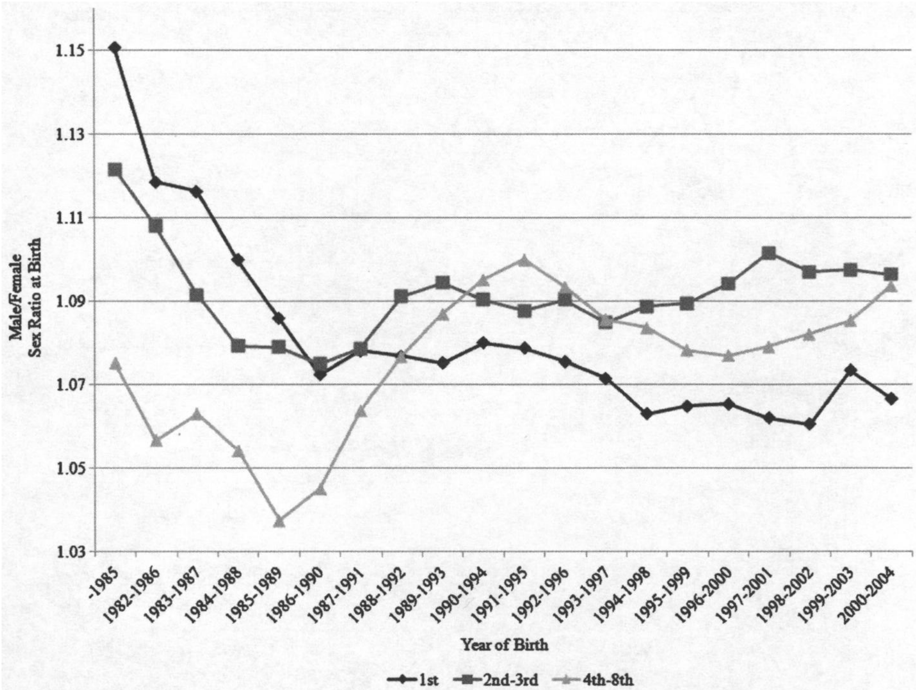

Fig. 1 Time trends in the reported male/female sex ratio at birth by birth order. Five-year smoothed birth groups. For example, "1982–1986" on the x-axis in the graph includes all children born in 1982 through 1986. The 95 % confidence interval is approximately +/− 0.01, where it is slightly smaller for more recent births and larger for more distant births. The first data point includes all births in 1985 and earlier. Data source is RCH II

India until the 1990s, making it unlikely that selective abortion is the cause of this high sex ratio. Second and third order births have higher than normal sex ratios going back to the early 1990s, approximately the time sex-selective abortion was becoming available, and approximately normal sex ratios for a brief period before this. The sex ratio is always lower for second- and third-order births in the more distant past (before 1990) than first-order births, and fourth- and higher-order births have even lower sex ratios before 1990. This is consistent with the idea of survival bias: we expect a first-born girl to have a stronger impact on fertility than a second- or third-born girl, while fourth- and higher-order female births should see little or no impact on fertility. Thus, if a rise in fertility causes a rise in mortality risk, we expect survival bias to be stronger for lower birth orders. This pattern is also consistent with recall bias: it is more likely for a mother to misreport births that are more distant in her past, so that we should expect more recall bias for first pregnancies than later pregnancies.[16] Even if overall in India the sex ratio of first births appears

[16] A similar pattern of rising sex ratios for births more distantly in the past has been reported in Bangladesh (Majumder et al. 1997).

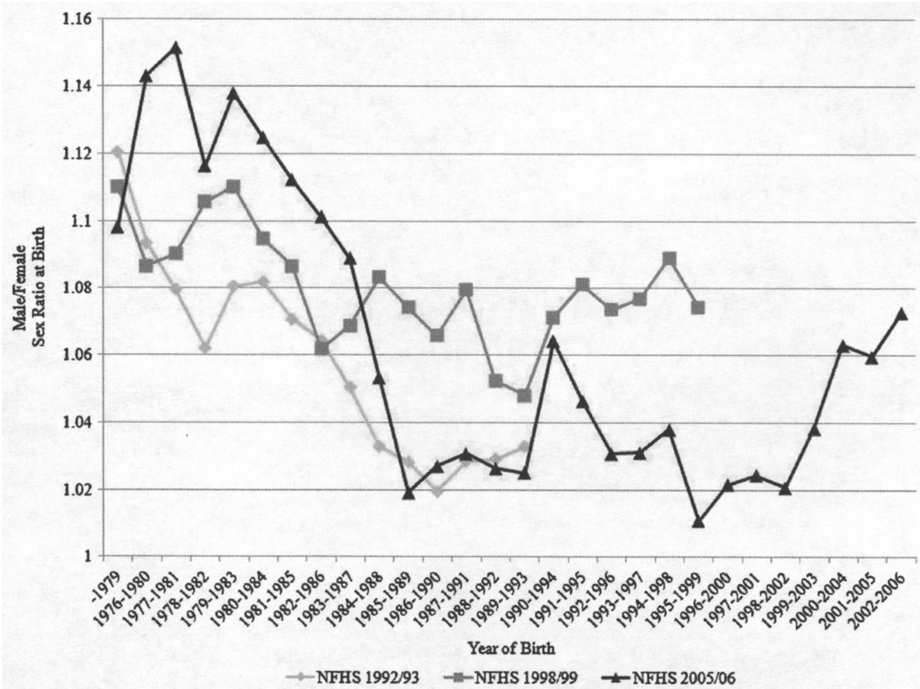

Fig. 2 Time trends in the reported male/female sex ratio at birth for first births. Five-year smoothed birth groups. The 95 % confidence interval is approximately +/− 0.025, where it is slightly smaller for more recent births and larger for more distant births. The first data point includes all births in 1979 and earlier. Data source is NFHS 1992/1993, 1998/1999, and 2005/2006

normal, there may be specific states of India where the sex ratio is unnaturally skewed towards males. This concern is addressed in Appendix C.

Another way to verify the existence of survival or recall bias is to check whether the reported sex ratio at birth in surveys is rising in the 1980s as surveys are taken later and later. As the cumulative effects of extra births cause higher mother mortality or more women forget or choose to ignore their true first births, we should see such a rise. Figure 2 uses the three Indian National Family Health Survey rounds in 1992/1993, 1998/1999, and 2005/2006 to look at trends in the sex ratios of first-borns over time.[17] The more recent the survey, the higher the sex ratio at birth in the 1980s. This finding is consistent with survival and recall bias.

As an additional test of the exogeneity of the sex outcome of the first birth, Table 2 shows descriptive statistics for the dependent and independent

[17]The NFHS surveys were implemented by IIPS with the support of the Indian Government's Ministry of Health and Family Welfare. The 1992/1993 round consists of 89,777 ever-married women, the 1998/1999 round consists of 89,199 ever-married women, and the 2005/2006 round consists of 124,385 women (married or not). All of the rounds restrict the age of respondents to 15–49. The relatively fewer number of births in the NFHS compared the RCH II cause wider fluctuations and larger confidence intervals.

Table 2 Descriptive statistics by first-birth outcome, mother age ≥ 35

	Entire sample	First-born boy	First-born girl	Difference
Dependent variables				
Mother's age (years)	38.99	38.98	39.00	0.02
Mother's education (years)	3.82	3.78	3.85	−0.07*
Father's education (years)	6.46	6.43	6.48	−0.05
Hindu (0/1)	0.820	0.819	0.820	−0.001
Muslim (0/1)	0.115	0.116	0.113	0.003
Scheduled caste (0/1)	0.176	0.176	0.177	−0.001
Scheduled tribe (0/1)	0.080	0.080	0.081	−0.001
Backwards class (0/1)	0.393	0.394	0.391	0.003
Rural (0/1)	0.638	0.637	0.639	0.002
Observations	152,059	80,714	71,345	
Independent variables				
Total children born	3.905	3.749	4.081	−0.332**
Proportion of male children	0.544	0.693	0.377	0.316**
Observations	152,059	80,714	71,345	
Mortality rate (%), boys	3.901	4.179	3.616	0.562**
Observations	118,763	60,424	58,339	
Mortality rate (%), girls	5.844	5.592	6.124	−0.532**
Observations	105,390	55,741	49,649	

No households with first-born twins. Sample weights used. N is slightly smaller for mother and father education and mother's age due to missing values. Mortality rate is the percent of boys or girls of birth order two or higher within a household who died between 1 and 60 months (multiplied by 100), conditional on having survived past 1 month of age. Data source is RCH II
$^{*}p = 0.10$ (significant); $^{**}p = 0.01$ (significant using t tests for age and education, and Pearson chi-squared tests for the other variables)

variables divided into sub-samples for households with a first-born son and those with a first-born daughter. These variables could affect child mortality and are exogenous with respect to child survival. On average, first-born boy households have parents who are less educated than parents in first-born girl households. This difference is only statistically significant for the mother's education. These differences are in accord with recall and survival bias, which make first-born boy households appear worse off than they would be without these biases. Mothers are older in first-born boy households, which is consistent with survival bias because women who had first-born sons are likely to live longer. All of these differences are small, and almost all are not statistically significantly different between first-born boy and first-born girl households. Thus, these descriptive statistics indicate that the bias in the data is not large.[18] Including these independent variables in the analysis helps to reduce this already small bias.

[18]We may expect a similar bias if infanticide was responsible for the above-normal sex ratios of first-births in older women since we would expect only the families with the worst socioeconomic situation to resort to such measures. Note that a first-born boy predicts approximately an extra 3 weeks between the first and second birth. There is evidence that shorter birth intervals cause low birth weight and, hence, higher mortality rates (Gribble 1993). This would bias the results in the opposite direction and result in higher mortality rates amongst first-born girl households.

The evidence shows that the sex outcome of a first-birth can be treated as a natural experiment, albeit with biases. Households that are not surveyed because of survival bias are likely to have higher child mortality rates compared to households where the mother is alive. Recall bias causes parents to not report first-born girls who died young and, again, these households will have high mortality rates. Both biases operate in the same direction. Since these forms of bias are more likely to occur for older parents, there is a trade-off in choosing an appropriate sample between fertility completion and bias. Since the focus of this paper is on fertility, I choose fertility completeness (the sample of mothers aged 35 years and older) and acknowledge the potential bias.

7 Estimates

Given the plausible exogeneity of the sex outcome of a first birth, I can now estimate Eq. 2. I show that a first-born son predicts fewer total children born and a higher proportion of male children. I then estimate the impact of a first-born son on male and female child mortality. A first-born son predicts higher male mortality but lower female mortality. The estimation results are shown in Table 3.

A first-born son predicts a decrease in the total number of children born by more than one third of a child. The average total number of children born is 3.9 for mothers aged 35 years and older. Thus, a first-born boy lowers the number of children in an average household by almost 10 %. This effect is much larger than that found in US data. For example, Angrist and Evans (1998) predict a fertility increase of 0.06 children if the first two children are of the same sex, while Dahl and Moretti (2008) estimate an increase of 0.007 children if the first-born is a girl. In addition, a first-born son is also a strong predictor of sibling sex composition. The proportion of sons in a household with a first-born boy is almost one-third higher than the proportion of sons in a household with a first-born girl.

A first-born boy lowers average girl mortality by 0.3 percentage points (statistically significant at the 1 % level). Although recall and survival bias will push this coefficient towards a positive number, the coefficient is negative. Hence, we can conclude that girls with a first-born older brother, with fewer siblings and a higher proportion of boys, have lower mortality rates than girls with a first-born sister. Fertility decisions in India, via the use of stopping rules, cause girls on average to be in households with more children, and in households with a higher proportion of girls. These fertility decisions translate into less resources for girls (the household size effect) and increased discrimination (the sex composition effect) and, hence, higher mortality rates among girls.

Boys are 0.5 percentage points less likely to survive in households with a first-born boy (statistically significant at the 1 % level). It is possible that bias in the data caused this positive coefficient. However, as shown above, the bias is likely small. In addition, if the sample is restricted to women under 35,

Table 3 OLS: the effect of a first-born boy on number of children, sex composition, and child mortality

	Total children born	Proportion of children male	Male mortality	Female mortality
First-born boy	−0.356**	0.304**	0.468**	−0.314**
	(0.011)	(0.003)	(0.088)	(0.110)
Mother's age	0.068**	0.000	0.046**	0.116**
	(0.002)	(0.000)	(0.016)	(0.020)
Mother years of school	−0.081**	0.000	−0.112**	−0.190**
	(0.002)	(0.000)	(0.012)	(0.016)
Father years of school	−0.043**	0.001**	−0.169**	−0.244**
	(0.002)	(0.000)	(0.013)	(0.017)
Rural	0.166**	0.003*	0.454**	1.167**
	(0.018)	(0.002)	(0.104)	(0.148)
R-squared	0.317	0.315	0.024	0.040
Clusters	593	593	593	593
Observations	150,781	150,781	117,734	104,494

Robust standard errors, clustered at district level, are reported in parentheses. All estimates include religion, caste, and state fixed effects as independent variables. All households are those where the mother's age is 35 years or older. No households with first-born twins. Child mortality is measured as the percentage of children (multiplied by 100) born at least 60 months before survey and died up to 60 months of age, conditional on surviving up to 1 month of age. Data source is RCH II
$*p < 0.05$; $**p < 0.01$

reducing this bias, the coefficient remains positive and significant, providing further support that bias is not the cause of the positive coefficient (estimate not shown). Thus, the results indicate that the sex composition effect is stronger than the household size effect for boys. These results also show that discrimination in larger, girl-proportioned households is not just anti-girl, it is also pro-boy. Thus, the reason that girls have higher childhood mortality rates than boys is not just that parents are more likely to neglect girls in larger, girl-proportioned households. In these households, parents actively improve the health of sons, making them better off than if the sons had fewer sisters.

In the sample of children of birth order two and higher whose mothers are 35 or older, approximately 52 out of 1,000 boys die between 1 and 60 months, while approximately 72 out of 1,000 girls die.[19] Thus, girls suffer 38 % higher child mortality than boys for this age group. If we unconditionally restrict ourselves to households with a first-born boy, the gap closes by about a third, so that girls only suffer 25 % higher child mortality than boys. Using the estimates in Table 3 to control for the other independent variables, if all children were in first-born boy households (taking all girl-first households and subtracting the estimated effect of being in a first-born boy household, γ, from boy and girl mortality respectively), the gap would close by about a quarter to slightly under 30 %, which represents a large reduction in the child mortality gap.

[19] This is the mortality rate of individual children as opposed to the mean of average child mortality within households reported in Table 2.

The results also provide insight into what happens when parents use selective abortion. If parents had used sex-selective abortion for their first pregnancy (i.e., they had first-born boys instead of first-born girls), the estimates predict that non-aborted girls would have lower mortality rates and boys would have higher mortality rates. The coefficient for male mortality is larger than the coefficient for female mortality. Hence, sex-selection could result in net higher child mortality, even if the gap between male and female child mortality would decrease. The results are partially in accord with that of Hu and Schlosser (2010), who examine whether sex-selective abortion improves girls' well-being and find that female nutrition improves. However, Hu and Schlosser (2010) do not find an effect of sex-selective abortion on female mortality. My results contrast that of Lin et al. (2008) who find that both boys and girls had lower mortality rates soon after selective abortion became legal in Taiwan in the mid-1980s. The magnitude effects of Lin et al. (2008) are much smaller than in the RCH II since mortality rates were already very low in Taiwan.

To put the negative effects of stopping rules in perspective, sex-selective abortion in India accounts for hundreds of thousands of missing women each year, while excess female mortality from stopping rules can account for tens of thousands of missing women each year. Thus, the excess mortality caused by stopping rules is large, but not nearly as large as the number of missing women caused by sex-selection. If sex-selection mitigates the negative effect of stopping rules, given the approximately half million selective abortions per year, I estimate that it would reduce missing women due to excess female mortality by thousands of women each year. Hence, the direct number of missing women caused by sex selection are two orders of magnitude greater than the reduction in missing women due to sex selection's reduction in female mortality.

7.1 Heterogeneity in the effects of a first-born son

On average, a first-born son predicts worse outcomes for boys and better outcomes for girls. However, these effects vary depending on the type of household. There are no systematic differences across regions (estimates not shown). However, I find differences between rural and urban households, as well as households with literate compared to illiterate parents. Since very few households exist where the mother is literate and the father is illiterate, I investigate three sub-samples: (1) both parents are illiterate, (2) only the father is literate, and (3) both parents are literate. The estimates are presented in Table 4. The statistically significant positive coefficient for male child mortality is robust to all sub-samples, giving further strength to the hypothesis that the sex composition effect outweighs the household size effect for boys. The coefficients for female mortality are of a similar magnitude as that in the main estimates. However, these coefficients are not statistically significant for the urban, both parents illiterate, and only father literate sub-samples. This may be due to the smaller sample size.

Coefficients of a larger magnitude indicate that there is a larger impact on child mortality. The estimates imply that stopping rules have a greater

Table 4 OLS: heterogeneous effects of a first-born boy on child mortality

	Rural		Urban			
	Male	Female	Male	Female	Male	Female
First-born boy	0.510**	−0.358*	0.418**	−0.210		
	(0.118)	(0.142)	(0.132)	(0.165)		
R-squared	0.025	0.040	0.017	0.031		
Observations	78,927	70,293	38,807	34,200		
	Both parents illiterate		Only father literate		Both parents literate	
First-born boy	0.472*	−0.402	0.819**	−0.314	0.319**	−0.274*
	(0.197)	(0.252)	(0.172)	(0.203)	(0.103)	(0.131)
R-squared	0.024	0.036	0.013	0.020	0.007	0.013
Observations	32,593	29,794	35,456	31,574	47,347	41,021

Robust standard errors, clustered at district level, are reported in parentheses. All households are those where the mother's age is 35 years or older. No households with first-born twins. Child mortality is measured as the percentage of children (multiplied by 100) born at least 60 months before survey and died up to 60 months of age, conditional on surviving up to 1 month of age. All estimations include household control variables and state fixed effects. The literate/illiterate sub-samples do not include parents' years of education as control variables. Data source is RCH II
$*p < 0.05$; $**p < 0.01$

impact on child mortality in rural compared to urban households. This result makes sense given that rural households tend to be poorer and have higher mortality rates than urban households. The coefficients are smaller when both parents are literate compared to when both parents are illiterate, which again makes sense as literate parents are likely richer and have lower mortality rates compared to illiterate parents. Interestingly, the coefficient for male mortality is largest when only the father is literate. This finding fits into the larger literature on bargaining power within the household. Fathers may have a stronger preference than mothers for stopping rules, and fathers will have more bargaining power the greater their education relative to their wives. Indeed, if the total number of children is the independent variable, a first-born daughter predicts 0.43 extra children when only the father is literate, compared to 0.33 for illiterate parents and 0.32 for literate parents (estimation table not shown). Thus, the fertility effects of stopping rules and subsequent discrimination may be larger if there is less equality in education. This finding is particularly important to policy makers, providing additional evidence that female education in India has significant positive externalities.

7.2 Robustness check: logit analysis

Average child mortality has discrete steps in it and values will be grouped at, for example, 0, 25, 33%, etc. Thus, although the theoretical model uses average child mortality, one may object that ordinary least squares (OLS) is not the correct estimation model. As a robustness check, I run a logit estimation, where the estimation equation is the same as in Eq. 2, except that the outcome, Y_{ij}, is now a 0 or 1 variable, which is 1 if the second-born child died between 1 and 60 months of age, conditional on surviving up to the first month of life. I only use the second-born child because virtually all households sampled have at least two children. By the age of 35, 95 % of women have two or more children. Thus, there should be little selection bias for this sample. However, we may be concerned with such bias for higher order births, since many parents will choose not to have more than two children. The results of the logit estimation are shown in Table 5.

Calculating the marginal effect of a first-born boy on the mean household, I find that a first-born boy increases the probability of a second-born boy dying by 0.27 percentage points and decreases the probability of a second-boy girl dying by 0.24 percentage points. Both coefficients are statistically significant at the 5 % level. These marginal effects are of a similar magnitude to the estimated coefficients in the OLS estimations.

7.3 Further analysis of results

A life table is shown in Fig. 3 in order to better understand the empirical results. The table shows how childhood survival varies by sex and by the outcome of the first birth. This figure has several salient features. First, the survival lines are consistent with the empirical results above: a first-born boy causes girls to have a higher chance of survival while causing a boy to have a lower chance of survival. Second, the survival gap between boys with an older brother compared to boys with an older sister is larger than the gap for girls. The relatively large differences in survival rates between boys of the different household types compared to girls may be due to recall and survival bias. In this case, children in boy-first households would seem to be worse off than they really are because some high mortality girl-first households are either missing or are misrecorded as boy-first. Third, although it is commonly believed that

Table 5 LOGIT: dependent variable = second order boy or girl dead (0/1)

	Male mortality	Female mortality
First-born boy	0.089**	−0.065*
	(0.038)	(0.033)
Mother's age	0.033***	0.044***
	(0.006)	(0.006)
Mother years of school	−0.074***	−0.084***
	(0.007)	(0.007)
Father years of school	−0.040***	−0.041***
	(0.005)	(0.004)
Rural	0.186***	0.173***
	(0.050)	(0.047)
Pseudo R^2	0.066	0.070
Clusters	592	592
Observations	75,062	68,524

Robust standard errors clustered by district in parentheses. All households are those where the mother's age is 35 years or older. No households with first-born twins. All estimates include religion, caste, and state fixed effects as independent variables. Data source is RCH II

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

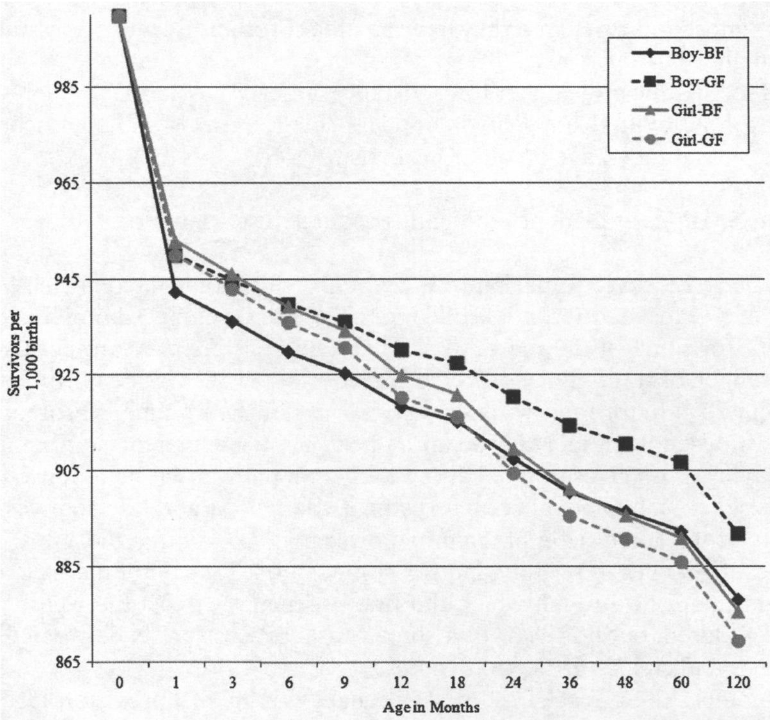

Fig. 3 Number of surviving children per 1,000 births, second order and higher, by sex and outcome of the first pregnancy. Boy-BF = male survival if first-born boy. Boy-GF = male survival if first-born girl. Girl-BF = female survival if first-born boy. Girl-GF = female survival if first-born girl. No households with first-born twins. The *darker lines* represent male survival, while the *lighter gray lines* represent female survival. *Solid lines* are households in which there is a first-born boy and *dotted lines* are households with a first-born girl. Each age point shows the proportion of all children who were born at least that many months before the survey was taken and who survived up until that age. Sample weights used. Data Source is RCH II

boys suffer higher mortality rates than girls in the first year of life (Hill and Upchurch 1995), in girl-first households, boys have higher survival rates than girls starting at 6 months of age. Fourth, the survival of girls in first-born boy households after age 24 months is very close to the survival of boys in first-born boy households.

The conclusion from the figure is striking: a large portion of the mortality gap between boys and girls of birth order two and higher would be eliminated if all of these children were born into boy-first households.[20] At age 60 months, the survival gap between boys and girls is large if they have an older sister. The

[20]The author does not, therefore, advocate that parents should selectively abort female first pregnancies. Rather, the graph points out that girls of birth order two and higher have lower mortality rates (and boys have higher mortality rates) if they have a first-born brother compared to a first-born sister. A sensible policy would be to implement programs that raise the relative value of daughters. Such a policy would both directly incentivize parents to invest more in the health of their daughters and indirectly allow an increase in girls' resources by lowering desired fertility.

gap is almost non-existent if they have an older brother. Because boys naturally have higher mortality rates than girls, if there were no bias against girls, we would see significantly higher boy mortality than girl mortality. So even though the gap for boy-first households appears small, there is still significant bias against girls if they have an older brother.

7.4 Vaccinations as evidence of health resource discrimination

There may be several mechanisms through which the outcome of the first pregnancy leads to differential child mortality. For example, sibling rivalry may account for some of the mortality results. Older sisters may protect and care for younger brothers but not do so for younger sisters. Older brothers may protect and care for their younger sisters, but not their younger brothers. The unitary household model may be unrealistic, and the actual mechanism may be that having a son gives mothers more bargaining power within a household. If mothers place a higher value on investing in daughters and less on investing in sons, then this increase in bargaining power may explain the mortality effects instead of changes in fertility and sex composition. I have not determined the exact mechanism through which the first pregnancy affects the well-being of future children, but it is clear that some causal process exists between fertility decisions and child mortality outcomes.

Examining the effect of the first pregnancy on health provision instead of directly on mortality allows us to further understand intra-household resource discrimination. Such an estimation may provide evidence that fertility decisions lead to health resource discrimination by parents as opposed to some other mechanism through which mortality could occur. The RCH II asks mothers about the vaccine status of their most recent one or two births after January 1, 1999 or January 1, 2001, depending on the phase of the survey.[21] Whether siblings are vaccinated is probably not an independent event. Thus to avoid this issue, I restrict the sample to only the single most recent non-twin birth of a mother. Seventy-six percent of recently born boys have been vaccinated, while 72 % of recently born girls have been vaccinated.[22] This vaccination gap is not large but, nonetheless, could be one of the causes of higher mortality amongst girls. Oster (2009), for example, shows that lack of vaccinations can account for as much as 20–30 % of excess female mortality in India.

The estimation equation is identical to Eq. 2. The effect on vaccinations is estimated in two ways: first, with the outcome of interest as a binary variable indicating whether the child received any vaccinations (multiplied by 100), and second, the total number of vaccinations received. Child age in months is included as an independent variable. If vaccinations are one way parents discriminate, we expect to see $\gamma < 0$ for males and $\gamma > 0$ for females. That is, if a boy is born first, this should cause later born boys to be vaccinated

[21] About 20 children were included even though they were born before the cutoff dates.

[22] Similar discrimination against girls in vaccinations is reported in Borooah (2004).

Table 6 OLS: effect of a first-born boy on vaccinations of most recently born children

	Vaccinated (0/1)* 100		# Vaccinations	
	Boys	Girls	Boys	Girls
Mother age ≥ 35	−1.439	0.784	−0.142**	0.088
	(0.949)	(1.019)	(0.070)	(0.070)
N	7,993	7,179	7,993	7,179
All ages	−1.594***	0.337	−0.137***	0.033
	(0.296)	(0.321)	(0.022)	(0.024)
N	73,156	63,525	73,156	63,525

Robust standard errors clustered by district in parentheses, coefficients on child age, mother's age, parent's education, religion, caste, rural/urban, and state dummy variables not shown. Most recently born child, birth order ≥ 2. No twins. Data source is RCH II

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

less and girls to be vaccinated more frequently. Because so few women aged 35 years and older have had a recent birth, restricting ourselves to this sample means large standard errors. Thus, I present separate results for mothers aged 35 years and older and for all mothers. The estimates are shown in Table 6.

As in the mortality estimates above, a first-born boy predicts 0.14 fewer vaccinations and a 1.4–1.6 percentage point smaller probability of being vaccinated for boys. However, the result for mothers older than 35 for the probability of being vaccinated is not statistically significant. The estimations predict 0.03–0.09 more vaccinations and a 0.3–0.8 percentage point larger probability of being vaccinated for girls, although the results for girls are not statistically significant. Thus, there is evidence that fertility decisions lead to discrimination in health resources by parents, at least among boys. One reason we might see an effect only for boys is that parents who discriminate against girls are already not vaccinating their daughters, while they are vaccinating their boys. Thus, when these parents have a first-born girl, this causes an increase in the vaccination of sons, but the vaccinations of daughters may not change.

8 Conclusion

This paper makes several contributions to the literature on fertility decisions and intra-household discrimination. It provides a theoretical framework to understand why economic incentives cause parents to follow fertility-stopping rules and how these decisions disadvantage girls on average. One new theoretical result is an economic explanation for why boys are better off with sisters and girls are better off with brothers. This paper provides evidence that sex composition must be taken into consideration when trying to understand the effects of fertility. I find that the sex of the first-born child explains about one quarter of the child mortality gap between boys and girls. Thus, fertility-stopping rules and the resulting resource discrimination may be a significant cause of excess girl mortality in India. Another implication of the estimates is that sex-selective abortions may counteract the effects of stopping rules, lowering the child mortality gap. However, the direct loss of women through sex selection is far larger than the indirect gain of women through lower child mortality. I also provide evidence that the allocation of health resources in the form of vaccinations are affected by stopping rules.

There are several policy implications from the above results. First, if policy makers want to specifically target households with the greatest discrimination, they should target large households with many daughters. The sub-sample estimates show that educating women may also reduce the negative consequences of stopping rules. In addition, the paper's theoretical framework can help us understand how changes in the future value of sons and daughters could affect fertility decisions and child mortality. If the relative value of daughters rises compared to sons, not only will parents want to directly increase their investment in daughters but also it may cause them to reduce their use of stopping rules. This would reduce fertility and allow even more resources to go to daughters.

Although the above framework can be used to help think about how to reduce excess female mortality, solutions are far from obvious. Although there have been some efforts to reduce the burden of marriage costs,[23] it seems unlikely that dowries will be eradicated in India in the foreseeable future, even though the practice has been officially illegal for almost 50 years. Policy makers will then need to focus on improving the economic situation of women or reducing the economic burdens of girls. The rise of women's microcredit groups is no doubt a start. Perhaps payments to households with girls tied to proof of medical care and education for girls is a viable solution. As a start, this paper provides some insight into the mechanisms through which girls are disadvantaged in India.

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Appendix A: Proofs of Propositions 1, 2, and 3

Assuming parents have stopped their fertility at N children and taking Eq. 1 above and substituting in the budget constraints yields the following maximization problem.

$$\max_{k_B,k_G} U_T = U_1(Y_1 - \pi N k_B - (1-\pi)Nk_G - NF) + U_2(Y_2 + \pi NDp(k_B) \\ -(1-\pi)NDp(k_G)) + U_S(p(k_B)\pi N + p(k_G)(1-\pi N))$$

[23]SKDRDP in Dharmasthala, India, for example, has held several free mass weddings which they have made attractive by using the strong religious influence of the Dharmasthala temple.

where k_B and k_G are health investments in boys and girls. $0 \leq \pi \leq 1$ is the proportion of boys. There are N total children. D is the size of the cost or benefit of daughters and sons, respectively. Y_1 and Y_2 are parents' income in periods 1 and 2. $0 \leq p(k_i) \leq 1$ is the number of surviving children of sex i, given health investment k_i. U_S is a concave function of number of surviving children. U_i and p are positive and strictly concave functions.

A.1 Proof of Proposition 1

Below are first-order conditions of the above utility function.

First-order condition 1:

$$\frac{\frac{\partial U_T}{\partial k_B}}{\pi N} = -U_1' + Dp'(k_B)U_2' + U_S'p'(k_B) = 0$$

First-order condition 2:

$$\frac{\frac{\partial U_T}{\partial k_G}}{(1-\pi)N} = -U_1' - Dp'(k_G)U_2' + U_S'p'(k_G) = 0$$

Below are the partial derivatives:

$$\frac{\frac{\partial^2 U_T}{\partial k_B^2}}{(\pi N)^2} = U_1'' + D^2 p'(k_B)^2 U_2'' + \pi N D p''(k_B) U_2' + U_S' p''(k_B) + U_S'' p'(k_B)^2 < 0$$

$$\frac{\frac{\partial^2 U_T}{\partial k_G \partial k_B}}{\pi(1-\pi)N^2} = U_1'' - D^2 p'(k_G)p'(k_B)U_2'' + U_S''p'(k_B)p'(k_G)$$

is positive if D is large enough.

$$\frac{\frac{\partial^2 U_T}{\partial k_G^2}}{(1-\pi)^2 N^2} = U_1'' + D^2 p'(k_G)^2 U_2'' - (1-\pi)NDp''(k_G)U_2' \\ + U_S'p''(k_G) + U_S''p'(k_G)^2,$$

which can be positive or negative depending on whether:

$$D^2 p'(k_G)^2 U_2'' - (1-\pi)NDp''(k_G)U_2'$$

is positive or negative. It is negative if D is large enough.

$$\frac{\frac{\partial^2 U_T}{\partial k_B \partial \pi}}{N} = (k_B - k_G)U_1'' + D^2 p'(k_B)(p(k_B) + p(k_G))U_2'' \\ + U_S''p'(k_B)p'(k_G)(p(k_B) + p(k_G)) < 0,$$

since $k_B - k_G > 0$

$$\frac{\frac{\partial^2 U_T}{\partial k_G \partial \pi}}{N} = N(k_B - k_G)U_1'' - ND^2 p'(k_G)(p(k_B) + p(k_G))U_2''$$
$$+U_S'' p'(k_G) p'(k_G)(p(k_B) + p(k_G)) > 0$$

if D is large enough.

Then

$$\frac{\partial k_B}{\partial \pi} = -\frac{Det\begin{vmatrix} \frac{\partial^2 U_T}{\partial k_B \partial \pi} & \frac{\partial^2 U_T}{\partial k_B \partial k_G} \\ \frac{\partial^2 U_T}{\partial k_G \partial \pi} & \frac{\partial^2 U_T}{\partial k_G^2} \end{vmatrix}}{Det\begin{vmatrix} \frac{\partial^2 U_T}{\partial k_B^2} & \frac{\partial^2 U_T}{\partial k_B \partial k_G} \\ \frac{\partial^2 U_T}{\partial k_G \partial k_B} & \frac{\partial^2 U_T}{\partial k_G^2} \end{vmatrix}} = -\frac{Det\begin{vmatrix} - & + \\ + & - \end{vmatrix}}{Det\begin{vmatrix} - & + \\ + & - \end{vmatrix}}$$

Both of the determinants are positive if D is large enough and $U_S' > DU_2'$, that is, if the marginal utility of survival is larger than the marginal consumption utility in period 2, making $\frac{\partial k_B}{\partial \pi} < 0$. (That is $\frac{\partial^2 U_T}{\partial k_B \partial \pi}\frac{\partial^2 U_T}{\partial k_G^2} > \frac{\partial^2 U_T}{\partial k_B \partial k_G}\frac{\partial^2 U_T}{\partial k_G \partial \pi}$ and $\frac{\partial^2 U_T}{\partial k_B^2}\frac{\partial^2 U_T}{\partial k_G^2} > \frac{\partial^2 U_T}{\partial k_B \partial k_G}\frac{\partial^2 U_T}{\partial k_G \partial k_B}$). By First-order condition 2, this must be true: $\frac{U_1'}{p'(k_G)} = U_S' - DU_2'$, which is positive because $\frac{U_1'}{p'(k_G)}$ is positive. And, thus, we have proved Proposition 1.

A.2 Proof of Proposition 2

$$\frac{\partial k_G}{\partial \pi} = -\frac{Det\begin{vmatrix} \frac{\partial^2 U_T}{\partial k_B^2} & \frac{\partial^2 U_T}{\partial k_B \partial \pi} \\ \frac{\partial^2 U_T}{\partial k_G \partial k_B} & \frac{\partial^2 U_T}{\partial k_G \partial \pi} \end{vmatrix}}{Det\begin{vmatrix} \frac{\partial^2 U_T}{\partial k_B^2} & \frac{\partial^2 U_T}{\partial k_B \partial k_G} \\ \frac{\partial^2 U_T}{\partial k_G \partial k_B} & \frac{\partial^2 U_T}{\partial k_G^2} \end{vmatrix}} = -\frac{Det\begin{vmatrix} - & - \\ + & + \end{vmatrix}}{Det\begin{vmatrix} - & + \\ + & - \end{vmatrix}}$$

The determinant in the denominator will be positive as above. If D is large enough the determinant in the numerator is negative and $\frac{\partial k_G}{\partial \pi} > 0$. This proves Proposition 2.

A.3 Proof of Proposition 3

To understand what happens to incentives to continue having children, I change the model's notation by letting $\pi N = B$ and $(1-\pi)N = G$.

$$U_T(k_B, k_G) = U_1(Y_1 - Bk_B - Gk_G - (B+G)F)$$
$$+U_2(Y_2 + BDp(k_B) - GDp(k_G)) + U_S(p(k_B)B + p(k_G)G)$$

So now there are explicitly B boys and G girls. Next we examine happens to parents' expected utility from having marginally more children (assumed with 50 % probability to be a boy and 50 % probability of being a girl). That is, how does $0.5\frac{\partial U_T}{\partial B} + 0.5\frac{\partial U_T}{\partial G}$ change with an increase in π, holding N constant.

$$\frac{\partial U_T}{\partial B} + \frac{\partial U_T}{\partial G} = (-k_B - k_G - F)U_1' + D(p(k_B) - p(k_G))U'2$$
$$+U_S'(p(k_B) + p(k_G))$$

If we raise the proportion of boys, as B goes up and G goes down, k_B goes down and k_G goes up (from above). Although it is ambiguous what happens to period 1 and survival marginal utility (depending on how much k_B decreases and how much k_G increases), period 2 marginal utility of consumption must fall. As long as D is large enough, this effect will dominate, causing parents to gain less utility from an extra child. Thus, we have proved Proposition 3.

Appendix B: Savings and credit

To illustrate as simply as possible how allowing parents to borrow against future dowry payments may reverse Proposition 1, I simplify the model by focusing solely on boys, so that the maximization problem becomes:

$$\max_{k_B,S} U_T(k_B, S) = U_1(Y_1 - Bk_B - S) + U_2(Y_2 + BDp(k_B) + RS)$$
$$+U_S(Bp(k_B))$$

where R is the rate of interest + 1. Let $\pi N = B$ and $(1-\pi)N = G$.

The first-order conditions are:

$$\frac{\partial U_T}{\partial k_B} = -BU_1' + DBp'(k_B)U_2' + U_S'Bp'(k_B) = 0$$
$$\frac{\partial U_T}{\partial S} = -U_1' + RU_2' = 0$$

Parents will always set S to satisfy

$$R = \frac{U_1'}{U_2'} = Dp'(k_B) + \frac{U_S'p'(k_B)}{U_2'}.$$

Parents invest in their sons until the return from investing in sons is equal to the return from saving. If $U_S(Bp(k_B)) = 0$, i.e., parents only care about the economic benefits of sons, then for however many sons they have, they will invest in their sons up until $Dp'(k_B) = R$. Thus, regardless of the number of sons, parents will not change their investment and child mortality will not change. If $U'_S > 0$, this is no longer an equilibrium. To see why, note that if B increases, ceteris paribus, U'_1 goes up and U'_2 goes down. If S is set such that again $R = \frac{U'_1}{U'_2}$, via borrowing against future child benefits, then $Dp'(k_B) + \frac{U'_S p'(k_B)}{U'_2} > R$, since U'_2 is smaller than before. Thus, in equilibrium, k_B must rise somewhat, giving the exact opposite result as in Proposition 1. Of course, if R is sufficiently large, parents will never borrow against future child benefits, and Proposition 1 will again hold. Since Proposition 2 stems from the overall wealth increase of extra sons, and not from the inter-period resource reallocation as for sons, the introduction of savings and credit should not change Proposition 2.

Appendix C: Heterogeneity in sex ratios at birth across states

India has large differences in sex ratios across states. For example, Punjab State has the worst child (age 0–6) sex ratio in India and the 1991 Indian census estimated this ratio at 1.14, rising to 1.26 in 2001. Thus, it is important to calculate the sex ratio at birth by state to make sure that some states with low sex ratios (e.g., Kerala) are not masking the sex ratios of states like Punjab. Table 7 presents sex ratios for the larger states of India for births within

Table 7 M/F ratio by large Indian state, age 0–10 at time of survey

State	First born	95 % CI
Jammu & Kashmir	1.364	(1.280, 1.454)
Uttaranchal	1.109	(1.041, 1.181)
Chhattisgarh	1.108	(1.048, 1.172)
Karnataka	1.108	(1.064, 1.154)
Assam	1.105	(1.055, 1.158)
Rajasthan	1.101	(1.064, 1.140)
Haryana	1.100	(1.052, 1.151)
Himachal Pradesh	1.079	(1.010, 1.120)
Kerala	1.076	(1.016, 1.139)
West Bengal	1.071	(1.020, 1.124)
Uttar Pradesh	1.064	(1.038, 1.090)
Punjab	1.064	(1.012, 1.118)
Madhya Pradesh	1.061	(1.028, 1.096)
Tamil Nadu	1.061	(1.021, 1.102)
Andhra Pradesh	1.046	(0.998, 1.096)
Bihar	1.040	(1.007, 1.075)
Maharashtra	1.039	(1.001, 1.079)
Gujarat	1.031	(0.987, 1.076)
Arunachal Pradesh	1.029	(0.974, 1.088)
Orissa	1.012	(0.973, 1.052)

Sample weights used. No households with first-born twins. Large states are those with more than 8,500 survey respondents. Data source is RCH II

Table 8 OLS: effect of a first-born boy on child mortality in states with a male/female sex ratio of first-borns < 1.07

	Male mortality	Female mortality
First-born boy	0.585***	−0.298*
	(0.128)	(0.161)
Mother's age	0.046**	0.138***
	(0.023)	(0.029)
Mother years of school	−0.143***	−0.239***
	(0.017)	(0.024)
Father years of school	−0.191***	−0.310***
	(0.017)	(0.023)
Rural	0.567***	1.343***
	(0.142)	(0.224)
R-squared	0.023	0.035
Clusters	325	325
Observations	64,283	56,878

Robust standard errors, clustered at district level, are reported in parentheses. All estimates include religion, caste, and state fixed effects as independent variables. All households are those where the mother's age is 35 years or older. No households with first-born twins. Child mortality is measured as the percentage of children (multiplied by 100) born at least 60 months before survey and died up to 60 months of age, conditional on surviving up to 1 month of age. Data source is RCH II

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$

10 years of being surveyed for the RCH II. The small states are not shown because their low sample size and correspondingly large confidence intervals make them uninformative. About half of the states have a sex ratio of first-borns above 1.07 (although 1.07 is within most of the states' confidence intervals). In order to ensure that the estimates in the paper are robust to the possibility that sex-selective abortion is occurring amongst first-borns in the states with first-born sex ratios above 1.07, the regressions in Eq. 2 are estimated with just the states with sex ratios below 1.07 in Table 7, and the results are similar to those reported in Table 3. The results are shown in Table 8.

Appendix D: Estimation that includes deaths in the first month of life

The results in Table 3 are robust to the inclusion of the deaths of children between 0 and 1 month. These deaths are included in Table 9 below. The results are similar to those above: a first-born boy predicts about a 0.4 percentage point increase in the probability of a higher order boy dying and about a 0.3 percentage point decrease in the probability of a higher order girl dying. A logit analysis analogous to the one performed as a robustness check for the OLS analysis yields similar estimates when deaths in the first month of life are included (estimations not shown).

Table 9 OLS: effect of a first-born boy on child mortality, including first month of life

	Male mortality	Female mortality
First-born boy	0.420*	−0.298*
	(0.082)	(0.105)
Mother's age	0.042*	0.108*
	(0.015)	(0.019)
Mother years of school	−0.107*	−0.183*
	(0.012)	(0.016)
Father years of school	−0.154*	−0.223*
	(0.012)	(0.016)
Rural	0.421*	1.040*
	(0.098)	(0.142)
R-Squared	0.023	0.038
Clusters	593	593
Observations	119,083	105,943

Robust standard errors, clustered at district level, are reported in parentheses. All estimates include religion, caste, and state fixed effects as independent variables. All households are those where the mother's age is 35 years or older. No households with first-born twins. Child mortality is measured as the percentage of children (multiplied by 100) born at least 60 months before survey and died up to 60 months of age. Data source is RCH II

$*p < 0.01$

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