

Measuring sex-selective abortion: How many women abort?*

Aditi Dimri[†] Véronique Gille[‡] Philipp Ketz[§]

July 4, 2023

Abstract

Current measurement of sex-selective abortion is based on a comparison of the sex ratio at birth with the natural sex ratio and provides us with the number of aborted female foetuses. This, however, does not tell us how prevalent the phenomenon is, i.e., how many women abort, which will differ from the number of aborted female foetuses when there is repeated sex-selective abortion. In this paper, we show that the number of women that abort *between two consecutive births* can be inferred using the sex ratio at birth and information on birth spacing. We use this result to study sex-selective abortion patterns in India over time and across birth orders, sibling compositions, and different socio-demographic/geographic groups. We find evidence of strong heterogeneity across samples, with the number of aborted female foetuses being up to 50% larger than the number of women that abort. Our findings suggest possible improvements in targeting of policies that aim at reducing sex-selective abortion.

JEL Classification: D10, J13.

Keywords: sex ratio, sex-selective abortion, missing girls, measurement, India.

*We thank François Maniquet and Jean-Marie Baland as well as seminar participants at CORE and IRES, Université Catholique de Louvain, Delhi School of Economics, University of Namur, and University of Warwick for helpful comments and suggestions.

[†]University of Warwick. E-mail address: aditidimri@gmail.com

[‡]IRD, UMR LEDa, PSL, Université Paris-Dauphine. E-mail address: veronique.gille@ird.fr

[§]Paris School of Economics - CNRS. E-mail address: philipp.ketz@psemail.eu

1 Introduction

Ever since the seminal work of Sen (1989), researchers have worked on estimating not only the number of missing women (Anderson and Ray, 2010) but also the number of missing female births or, equivalently, the number of aborted female fetuses (see, e.g., Bongaarts and Guilmoto, 2015; Bhalotra and Cochrane, 2010; Chao et al., 2019; Klasen and Wink, 2003). Estimates of the latter are based on the difference between the sex ratio at birth and the hypothesized, or otherwise estimated or calibrated, natural sex ratio.¹ However, little is known about how prevalent sex-selective abortion is, i.e., how many women, or households, abort.² In particular, we note that the number of women that abort will be different from the number of aborted female fetuses if some women abort repeatedly. While the number of women that abort could, in theory, be computed from administrative data from abortion clinics or self-reported survey data, these numbers are generally unreliable. As sex-selective abortion is illegal in most countries, it is likely to be carried out at uncertified/unregistered facilities (Grimes et al., 2006), and for abortions performed in registered abortion clinics it is generally not known whether they are performed for the purpose of sex selection (Chandra et al., 2021). Similarly, sex-selective abortion has been shown to suffer from severe under-reporting in survey data, arguably because of its illegality and the stigma attached to it (Stillman et al., 2014). In this paper, we contribute to the effort of improving the measurement of sex-selective abortion by adding a new measure: the number, or share, of women that abort *between two consecutive births*. It is based on the simple empirical observation that a large sex ratio at birth or, equivalently, a large proportion of male births (in exceedance of the natural probability of male birth) is concurrent with differences in the distribution of birth spacing depending on the sex of the next-born child, cf. Figure 1.³

Figure 1 shows the empirical distribution functions (*edfs*) of spacing by sex of the next-born in two different samples of women in India. In panel (a), where the proportion of male births is 0.517 and, thus, not “too far” from the natural probability of male birth,⁴ the *edfs* of spacing for boys and girls are almost indistinguishable. In panel (b), on the other

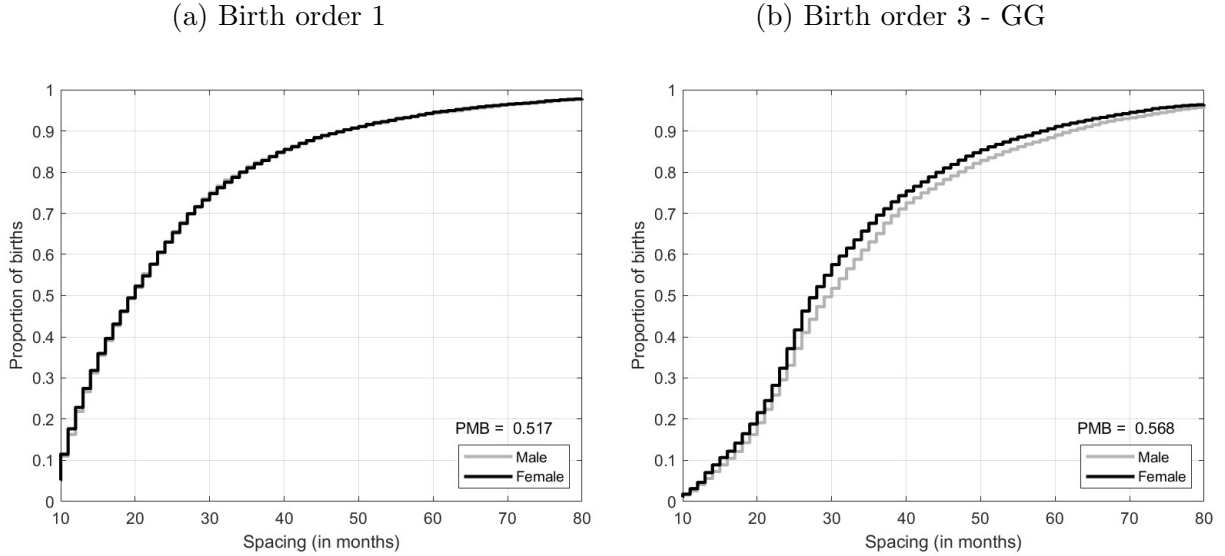
¹For example, Chao et al. (2019) thus estimate that, between 1970 and 2017, 45 million female births were missing in the world and that China and India account for 51% and 46% of these, respectively. In a comprehensive policy report, Guilmoto (2012) lists other countries with “distorted” sex ratios such as Albania, Armenia, Azerbaijan, Georgia, Montenegro, Pakistan, and Vietnam.

²In this paper, we do *not* model the decision making process underlying sex-selective abortion and, therefore, refer to our observational units as women or households interchangeably, without taking a stance on who the decision maker is.

³We use the term “next-born” throughout the paper to refer to the child born *after* the spacing (time) under consideration. For example, when we discuss spacing between the first and second child, the sex of the next-born refers to the sex of the second child.

⁴Based on Chao et al. (2019) and Dubuc and Coleman (2007), we take it to be equal to 0.513.

Figure 1: Empirical distribution functions of spacing by sex of the next-born



Note: Panel (a): Empirical distribution function (*edf*) of spacing at birth order 1, i.e., the time between marriage and birth of the first child, by sex of the first-born. Panel (b): *edf* of spacing at birth order 3, i.e., the time between the births of the second and third child, when the first two children are girls (GG) by sex of the third-born. Both *edfs* pertain to literate women during the period 1988–1995; see Section 4 for a detailed data description. In both panels, the proportion of male births (PMB) is indicated in the bottom-right corner.

hand, where the proportion of male births is much larger with 0.568, the *edfs* of spacing for boys and girls are clearly distinct. This is not accidental: differences in the distribution of spacing by sex of the next-born arise *because* of sex-selective abortion. To gain intuition for this “mechanical” implication of sex-selective abortion, first note that each sex-selective abortion increases not only the proportion of male births but also spacing, because it takes time to determine the sex of the foetus in utero and to get pregnant again. Next, assume for simplicity that the natural probability of male birth equals $1/2$ and that the share of women that abort (at a given birth order) also equals $1/2$. Furthermore, assume that the women that abort do so indefinitely until they have a boy. Under these assumptions, the proportion of male births is $3/4$ (in expectation). Furthermore, all girls as well as $(\frac{1}{2}/\frac{3}{4} =)$ $2/3$ of the boys have “short” spacing, i.e., spacing that was not prolonged by a sex-selective abortion. The remaining boys, however, have “longer” spacing, as they are born after one or more sex-selective abortions. Therefore, boys are *on average* born later than girls, i.e., the distribution of spacing differs by sex of the next-born.

More generally, the difference in the distribution of spacing between boys and girls depends on the share of women that sex-selectively abort and how many times they do so.

We formalize this relationship by means of a simple statistical model.⁵ An immediate by-product of our model is a simple test for the presence of (repeated) sex-selective abortion. An attractive feature of the test is that it only uses differences in average spacing between boys and girls and, therefore, dispenses with the need to specify the natural probability of male birth, which is a contested topic (Chao et al., 2019). We, then, propose an estimator for our model that *does* rely on the natural probability of male birth but enables us to infer the share and, thus, the number of women that abort as well as the share of women that abort a second time (when again pregnant with a female foetus after a first abortion)—assuming that women abort at most twice. While we are not the first to note that sex-selective abortion impacts spacing (see, e.g., Pörtner, 2022; Anukriti et al., 2022), the fact that it does so depending on the sex of the next-born and that it can be used to measure the prevalence of sex-selective abortion is, to the best of our knowledge, new to the literature.

We use our model to study the evolution of sex-selective abortion patterns in India over time, using data from the five rounds of the Demographic and Health Surveys (1992–93, 1998–99, 2005–06, 2015–16, and 2019–2021) and the 2002–04 round of the District Level Household & Facility Survey. While sex-selective abortion is practiced in several countries (Guilmoto, 2012), India has been estimated to account for 46% of the aborted female foetuses worldwide over the period 1970–2017 (Chao et al., 2019) and, thus, constitutes an interesting case study. Our analysis is performed at several birth orders, for different sibling compositions, and is broken down according to socio-demographic and geographic factors. In particular, we consider literate and illiterate women, women in urban and rural areas, and women in the north and south of India. At birth order 1, in line with the literature, we find little to no evidence of sex-selective abortion. At birth orders 2 and 3, we find evidence of sex-selective abortion when all previous siblings are girls. Our estimation results show that the share of women that abort is increasing over time and that it is larger at birth order 3 than at birth order 2. We also find strong heterogeneity across socio-demographic/geographic groups. For example, we find that literate women (women in urban areas) are more likely to abort than illiterate women (women in rural areas). Furthermore, the aforementioned test provides strong evidence of *repeated* sex-selective abortion at birth order 3, which is also corroborated by our estimation results. In some samples, the share of aborted female foetuses is estimated to be 50% larger than the share of women that abort, highlighting the empirical relevance of our proposed measure.⁶

Beyond the intrinsic value of knowledge of the prevalence of sex-selective abortion, our

⁵In our model, we abstract from the fact that total fertility or abortion behavior at other birth orders may interact with the decision to abort at any given birth order.

⁶The results are reported in terms of shares rather than in terms of numbers for ease of comparison between groups over time.

proposed measure may also prove useful for policy targeting. Unbalanced sex ratios have widely acknowledged adverse societal consequences (see Anukriti et al., 2022, for a review), which is why governments across the globe have tried to prevent sex-selective abortion through policies like banning pre-natal sex screening, punishing violations, and conditional cash transfers (CCTs) “for” girls (Kumar and Sinha, 2020). However, the effectiveness of such policies can be low; see, e.g., Kumar and Sinha (2020) and references therein for an account on CCTs. If repeated sex-selective abortion is indicative of a higher utility of having a boy net of costs (monetary and/or non-monetary), our estimates of the share of women that abort a second time (when again pregnant with a female foetus after a first abortion), which vary across samples, suggest that it maybe possible to improve the effectiveness of CCTs through better targeting. For example, reducing sex-selective abortion in groups with large shares of women that abort a second time, such as literate women whose first two children are girls, may require larger cash transfers.

Our model and findings also call for more caution in the interpretation of sex ratios at birth. The sex ratio at birth is often used as a proxy for son preference, for example, in the literature on the origins of son preference (Alesina et al., 2018; Goli et al., 2022; Mavisakalyan and Minasyan, 2023; Qian, 2008) or in the literature on the societal impact of son preference (Hwang et al., 2019). These literatures implicitly make the assumption that two, for example, geographical areas with the same sex ratio have (approximately) the same level of son preference. As this paper shows, however, the number of women that abort may differ across these two geographical areas.

The rest of the paper is organized as follows. Section 2 provides the contextual background for sex-selective abortion in India. Section 3 introduces our model, illustrates some of its implications, and presents a maximum likelihood estimator. Sections 4 and 5 present the data and our empirical findings, respectively, while Section 6 concludes. Additional material, including proofs, can be found in the Appendix.

2 Contextual background: sex-selective abortion in India

Abortion has been legal in India since the *Medical Termination of Pregnancy Act, No. 36, Government of India (1971)*, which allows a pregnancy to be terminated up to 20 weeks gestation by registered allopathic medical practitioners at certified abortion facilities. Sex-selective abortion, however, is not legal and is controlled through the *Pre-Natal Diagnostic Techniques (Regulation and Prevention of Misuse) Act, No. 57, Government of India (1994)*

which prohibits the misuse of antenatal diagnostic tests for the purpose of sex determination. It prohibits the advertisement of such tests, requires registration of all facilities that use them, and prohibits revealing the sex of the foetus to the expectant parents.

Despite this law, sex-selective abortion is widely practiced. Chao et al. (2019), for example, estimate the number of missing female births in India between 1970 and 2017 to be 20.7 millions. While the 1994 ban on sex-selective abortion seems to have slowed down the increase in the use of sex-selective abortion for poorer households (Rastogi and Sharma, 2022), the imbalance in the sex ratio at birth has continued to increase. Saikia et al. (2021), for example, estimate that the number of missing female births has increased by one million every 10-year periods, from 3.5 millions between 1987 to 1996 to 5.5 millions between 2007 and 2016. Two main explanations have been brought forward to explain this increase. First, sex determination during pregnancy has become more easily accessible and cheaper since the mid-1990s, following increases in imports and domestic production of ultrasound machines (Anukriti et al., 2022). Second, desired total fertility (i.e., total number of children) has decreased (Baland et al., 2022). As the probability to have at least one son decreases with a decrease in total fertility, households that want to have at least one son are more likely to use sex-selective abortion. Jayachandran (2017) estimates that between one third and one half of the increase in the child sex ratio between 1981 and 2011 can be explained by this change in desired total fertility.⁷

Furthermore, there is heterogeneity in the occurrence of sex-selective abortion across regions and demographic groups in India. Sex-selective abortion is more common in northern India (Saikia et al., 2021) and urban areas (Pörtner, 2022) as well as among wealthier households and more educated women (Bhalotra and Cochrane, 2010). While, according to Diamond-Smith and Bishai (2015), differences across regions in terms of child sex ratios have decreased between 1991 and 2001, differences between demographic groups in terms of the number of missing female births have increased over the same period (Jha et al., 2011).

The occurrence of sex-selective abortion also depends on the birth order and the sex composition of previous children. The consensus in the literature is that there is no sex-selective abortion at birth order 1 (Dahl and Moretti, 2008; Milazzo, 2018; Heath and Tan, 2018), although there has been some evidence to the contrary in recent years (Saikia et al., 2021). At higher birth orders, sex-selective abortion is more common in households that previously only had girls, reflecting the widespread preference for having at least one son (Bhalotra and Cochrane, 2010). While the number of missing female births used to be highest at birth order 3, Saikia et al. (2021) find that in recent years (2007–2016) more

⁷Jayachandran (2017) uses the child sex ratio, i.e., the sex ratio among the 0–6 years old, as a proxy for the sex ratio at birth.

female births are missing at birth order 2.

3 A model for spacing in the presence of sex-selective abortions

In this section, we first introduce our model. Then, we show that our model implies different spacing by sex of the next-born in the presence of sex-selective abortion. Next, we present a proposition that can be used to test for the presence of (repeated) sex-selective abortion. Lastly, we present our maximum likelihood estimator for estimating the share of women that abort.

3.1 The model

The time between two consecutive births, or simply spacing, is denoted by T_b^A (*time to birth*) and depends on the unobserved, or latent, number of sex-selective abortions, $A \in \{0, 1, \dots, N_0\}$, performed between the two births, where N_0 denotes the (known) maximal number of “possible” abortions. We sometimes suppress the dependence of T_b^A on A and write $T_b = T_b^A$. Here and in what follows, we let capital letters denote random variables and the corresponding lower case letters their (possible) realizations. We postulate the following model

$$T_b^a = T_w + \sum_{k=1}^a (T_s + T_{c,k}) + T_p.$$

Here, T_w denotes the *waiting time* (until conception), i.e., the time that the household, after the birth of a child, waits before trying to conceive again *plus* the time it takes to conceive. T_s denotes the *time to screening*, i.e., the time it takes from the moment of conception until the sex of the foetus is known.⁸ This is the time the household has to wait before it can perform a sex-selective abortion (if applicable). We do not index T_s by the abortion cycle, because we take it to be constant. $T_{c,k}$ denotes the *time to conception* after the k^{th} abortion, i.e., the time it takes for the woman to get pregnant after having aborted k times. Lastly, T_p denotes the *time of pregnancy*, which we take to be equal to nine months. For $a = 0$, i.e., when the household does not abort, birth spacing equals $T_w + T_p$.

To complete the model, we introduce its main parameters, $\alpha_k \in [0, 1]$ for $k \in \{1, \dots, N_0\}$, where α_k denotes the probability that a household performs the k^{th} sex-selective abortion

⁸For simplicity, we assume that every household knows the sex of the foetus. However, the implications of the model are identical if we assume that a household that does not, or would not, sex-selectively abort does not know the sex of the foetus.

when pregnant with a female foetus (for the k^{th} time). As the α s are not household specific, we also refer to them as (population) shares, i.e., we say that α_1 is the share of women that abort (when pregnant with a female foetus), α_2 is the share of women that abort a second time (when again pregnant with a female foetus after a first abortion), etc. For what follows, it is convenient to introduce α_0 which is set equal to one and α_{N_0+1} which is set equal to zero. Furthermore, we let $N \leq N_0$ denote the maximal number of abortions in the population, i.e., N is such that $\alpha_k > 0$ for $k \in \{1, \dots, N\}$ and $\alpha_{N+1} = 0$.

The above model makes several assumptions. First, we assume that, after an abortion, the household tries to conceive again without any additional waiting time.⁹ Second, we assume that the natural probability of male birth is equal to the probability of getting pregnant with a male foetus. This implies that miscarriages and abortions not performed for the purpose of sex-selection are equally likely for male and female foetuses such that any associated delay can be thought of as being absorbed by T_w and $T_{c,k}$.¹⁰ In what follows, we also assume that $T_{c,k}$ is i.i.d. across k , with $T_{c,k} \sim T_c$.¹¹ Even if there is heterogeneity, we assume it to be independent of the abortion decision. Lastly, we assume T_w to be independent of the willingness to abort. While households may have a different T_w depending on whether they would abort if pregnant with a female foetus, we do not model it. However, we discuss some of the implications of this assumption in Section 3.3.

3.2 Spacing by sex of the next-born

The above model implies that sex-selective abortion impacts the distribution of spacing. Moreover, it does so differently depending on the sex of the next-born, as we illustrate in what follows.

3.2.1 The case with at most one sex-selective abortion ($N_0 = 1$)

If there is no sex-selective abortion, the distributions of spacing if the next-born is a boy and if it is a girl are equal, i.e., $T_b|Y = 1 \sim T_b|Y = 0$, where \sim denotes “is distributed as” and where $Y \in \{0, 1\}$ denotes the sex of the next-born, with $Y = 0$ indicating the birth of a girl and $Y = 1$ indicating the birth of a boy. But if there is sex-selective abortion, the distribution

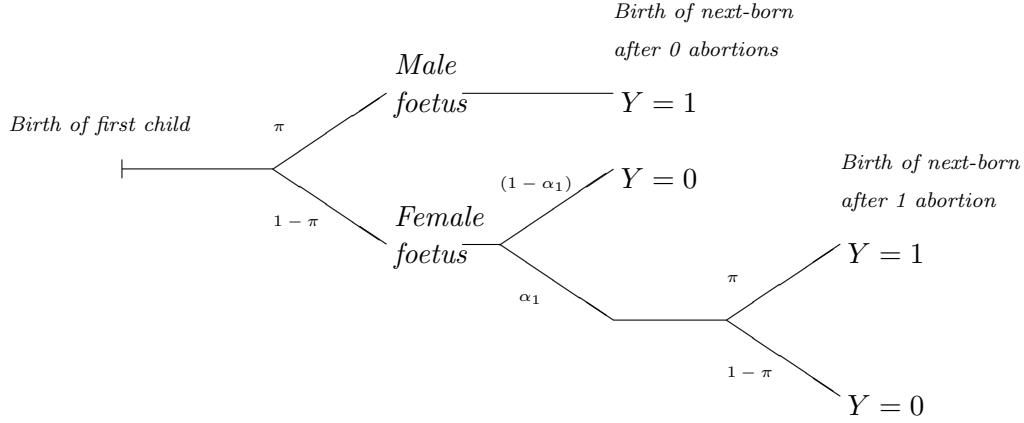
⁹This assumption is based on the fact that the decision to have another child has already been made before the abortion and that ovulation typically returns within one month after an abortion (see, e.g., the “Abortion Care guideline” of the World Health Organization, 2022).

¹⁰Orzack et al. (2015) find that the sex ratio at conception is, in fact, balanced, but that the natural sex ratio at birth is male-biased due to excess female mortality during pregnancy. Given the rationale of our model, one may therefore worry that time to birth naturally differs by sex of the next-born. However, panel (a) of Figure 1 suggests that any such difference is practically immaterial.

¹¹This assumption is supported by Oster (2022) who finds that time to conception at birth order 1 only explains 11% of the variation in time to conception at higher birth orders.

of spacing will be different depending on the sex of the next-born, i.e., $T_b|Y = 1 \not\sim T_b|Y = 0$, where $\not\sim$ denotes “is not distributed as”.¹² To illustrate this, consider Figure 2, which plots all possible “paths” to birth under the assumption that women abort at most once, i.e., $A \in \{0, 1\}$.¹³ Here and in what follows, π denotes the probability of getting pregnant with a male foetus, which we, as mentioned above, assume to be equal to the natural probability of male birth (such that the natural sex ratio is given by $\frac{\pi}{1-\pi}$).

Figure 2: Paths to birth with one abortion



At conception, a woman gets pregnant with a male foetus with probability π and pregnant with a female foetus with probability $1 - \pi$. If she is pregnant with a male foetus, assuming there is no abortion other than sex-selective, a boy is born after 9 months, i.e., $T_b = T_b^0$. If she is pregnant with a female foetus, the household aborts with probability α_1 and with probability $1 - \alpha_1$ the household keeps the girl. If the household keeps the girl, she is born after the same time as the boy, i.e., $T_b = T_b^0$. If the female foetus is aborted, then a boy or a girl is born later, i.e., $T_b = T_b^1$.

Given that $A \in \{0, 1\}$, we can write $T_b = T_b^1 A + T_b^0(1 - A)$. In words, birth spacing is a mixture of time to birth with one abortion, T_b^1 , and time to birth with zero abortions, T_b^0 . Since T_b^1 first-order stochastically dominates T_b^0 , it is easy to see that $T_b|Y = 1 \not\sim T_b|Y = 0$ if T_b^1 and T_b^0 have different “mixture weights” depending on the sex of the next-born, i.e., if

¹²Formally, two random variables, X_1 and X_2 , have the same distribution ($X_1 \sim X_2$) if $P(X_1 < x) = P(X_2 < x)$ for all $x \in \mathcal{X}$, where $\mathcal{X} = \mathcal{X}_1 \cup \mathcal{X}_2$ and where \mathcal{X}_i denotes the support of X_i with $i \in \{1, 2\}$. Similarly, X_1 and X_2 have different distributions ($X_1 \not\sim X_2$) if $P(X_1 < x) \neq P(X_2 < x)$ for some $x \in \mathcal{X}$.

¹³Guilmoto et al. (2020) consider a “probabilistic” model of sex-selective abortion behavior at a given “parity” similar to ours. However, they do not analyze the implications of their model for spacing.

$P(A = 1|Y = 1) \neq P(A = 1|Y = 0)$.¹⁴ From Figure 2, it follows that

$$P(A = 1|Y = 1) = \frac{P(A = 1, Y = 1)}{P(Y = 1)} = \frac{(1 - \pi)\alpha_1}{(1 - \pi)\alpha_1 + 1} \quad (1)$$

and

$$P(A = 1|Y = 0) = \frac{P(A = 1, Y = 0)}{P(Y = 0)} = \frac{(1 - \pi)\alpha_1}{(1 - \pi)\alpha_1 + 1 - \alpha_1}. \quad (2)$$

Therefore, $P(A = 1|Y = 1) \neq P(A = 1|Y = 0)$ as long as $\alpha_1 > 0$ or, equivalently, $N = 1 (= N_0)$, i.e., as long as there is sex-selective abortion. We conclude that in the presence of sex-selective abortion spacing differs by sex of the next-born.

3.2.2 The general case ($N_0 \geq 1$)

More generally, our model implies that

$$P(A = a, Y = 1) = (1 - \pi)^a \prod_{k=0}^a \alpha_k \quad (3)$$

and

$$P(A = a, Y = 0) = (1 - \pi)^a (1 - \alpha_{a+1}) \prod_{k=0}^a \alpha_k. \quad (4)$$

By definition, $P(Y = 1) = \sum_{a=0}^{N_0} P(A = a, Y = 1)$ and $P(Y = 0) = \sum_{a=0}^{N_0} P(A = a, Y = 0)$.

3.3 A partial test for the presence of (repeated) sex-selective abortion

Next, we derive a proposition from our model that can easily be applied to the data to test for (repeated) sex-selective abortion without imposing any further assumptions. In particular, the proposition only exploits mean spacing by sex of the next-born and, thus, does not require any assumptions on the natural probability of male birth, nor on the distributions of T_w and T_c .

Proposition 1.

- (i) If $E(T_b|Y = 0) \neq E(T_b|Y = 1)$, then $N > 0$ or, equivalently, $\alpha_1 > 0$.
- (ii) If $E(T_b|Y = 0) < E(T_b|Y = 1)$, then $N > 1$ or, equivalently, $\alpha_1, \alpha_2 > 0$.

¹⁴To see this, note that

$$P(T_b < t|Y = y) = P(T_b^1 < t)P(A = 1|Y = y) + P(T_b^0 < t)(1 - P(A = 1|Y = y)).$$

Proposition 1(i) can be used to detect sex-selective abortion and therefore complements the sex ratio. If mean spacing differs by sex of the next-born, then there is sex-selective abortion.¹⁵ The advantage of using (mean) spacing as an indicator of sex-selective abortion is that it is independent of the natural sex ratio, which is not always easily agreed upon. Proposition 1(ii) can be used to detect *repeated* sex-selective abortion. If mean spacing for girls is lower than mean spacing for boys, then there is repeated sex-selective abortion, i.e., a strictly positive fraction of the population aborts a second time if again pregnant again with a female foetus. We note that Proposition 1 provides *sufficient*, but not necessary, conditions. For example, it is possible that repeated sex-selective abortion is present in the population ($N > 1$) but that $E(T_b|Y = 0) > E(T_b|Y = 1)$. It is in that sense that the tests based on Proposition 1 are only *partial*.

As mentioned before, the model and hence Proposition 1 assume that T_w is independent of whether a household aborts if pregnant with a female foetus. In Appendix A, we show that Proposition 1 continues to hold true when T_w is allowed to depend on whether a household aborts, or rather would abort, if pregnant with a female foetus as long as the expected *waiting time*, $E(T_w)$, is (weakly) smaller, or “shorter”, for a household that aborts if pregnant with a female foetus than for a household that does not. The latter condition, albeit not testable, seems likely to hold, as households that would abort if pregnant with a female foetus may anticipate the potentially longer spacing that an abortion implies.

3.4 Maximum likelihood estimation

In order to estimate the model and its main parameters, i.e., the different shares of women that abort, α , we rely on the principle of maximum likelihood. We assume that T_w and T_c are independent and gamma-distributed, with shape parameters γ_w and γ_c and scale parameters β_w and β_c .¹⁶ This distributional assumption is not only flexible but also allows us to obtain an analytical expression for the likelihood function, avoiding computationally expensive simulation-based estimation. In particular, the individual likelihood function is given by

$$L(\theta; t, y) = \sum_{a=0}^{N_0} f_{T_b^a}(t; \gamma_w, \beta_w, \gamma_c, \beta_c) P(Y = y, A = a; \alpha),$$

¹⁵More generally, our model implies that if $P(T_b < t|Y = 0) \neq P(T_b < t|Y = 1)$ for at least some $t \in \mathcal{T}$, then $N > 0$. Therefore, an alternative, potentially more powerful test for the presence of sex-selective abortion would consist in testing whether the two conditional distributions are equal. Here, we focus on the “difference-in-means” for its simplicity.

¹⁶Recall that the *time to pregnancy*, T_p , is taken equal to 9 and that the *time to screening*, T_s , is also taken equal to a fixed value, t_s . In particular, we set $t_s = 5$ and note that our results are robust to different values of t_s ; the corresponding estimation results are available upon request.

where $\theta = (\alpha', \gamma_w, \beta_w, \gamma_c, \beta_c)'$ and where

$$f_{T_b^a}(t; \gamma_w, \beta_w, \gamma_c, \beta_c) = \begin{cases} f_{\Gamma}(t - 9; \gamma_w, \beta_w) & \text{if } a = 0 \\ f_{\Sigma\Gamma}(t - 9 - t_s a; \gamma_w, \beta_w, \gamma_c a, \beta_c) & \text{if } a > 0 \end{cases}$$

denotes the probability density function (*pdf*) of T_b^a (for a given a). Here, $f_{\Gamma}(\cdot; \gamma, \beta)$ and $f_{\Sigma\Gamma}(\cdot; \gamma_1, \beta_1, \gamma_2, \beta_2)$ denote the *pdf* of a gamma-distributed random variable (with shape parameter γ and scale parameter β) and the *pdf* of the sum of two independent gamma-distributed random variables (with shape parameters γ_1 and γ_2 and scale parameters β_1 and β_2), respectively; see Appendix B for details. Note that $P(Y = y, A = a; \alpha)$, where we have made the dependence on α explicit, is given in (3) and (4) for $y = 1$ and $y = 0$, respectively.

With $L(\theta; t, y)$ thus defined, we could in principle estimate θ by maximizing the log-likelihood function, $\sum_{i=1}^n \log L(\theta; t_i, y_i)$, over the parameter space $[0, 1]^{N_0} \times [0, C]^4$ for some large $C < \infty$, where $i = 1, \dots, n$ indexes the households in the estimation sample. Here, in order to “aid” estimation we instead calibrate γ_c and β_c using “external” data; see Appendix B for details. Furthermore, we impose that $N_0 = 2$ and, with a slight abuse of notation, let $\theta = (\alpha_1, \alpha, \gamma_w, \beta_w)'$ with the understanding that $L(\theta; t_i, y_i)$ denotes $L((\theta', \tilde{\gamma}_c, \tilde{\beta}_c)'; t_i, y_i)$, where $\tilde{\gamma}_c$ and $\tilde{\beta}_c$ denote the calibrated values of γ_c and β_c , respectively. Formally, our “maximum likelihood” estimator is defined as

$$\hat{\theta} = \arg \max_{\theta \in \Theta} \sum_{i=1}^n \log L(\theta; t_i, y_i),$$

where $\Theta = [0, 1]^2 \times [0, C]^2$.

An important comment about our estimation problem is in order, namely that α_2 is not identified when α_1 is equal to zero, in the sense that $\sum_{i=1}^n \log L(\theta; t_i, y_i)$ does not depend on α_2 when $\alpha_1 = 0$, cf. Assumption A in Andrews and Cheng (2012) (AC hereafter). Intuitively, we cannot know, or identify, the share of women that abort a second time if none of them abort a first time. By continuity, we also have that α_2 is weakly identified when α_1 is close to zero *relative* to the sample size, n . More precisely, the identification strength of α_2 is governed by $\sqrt{n}\alpha_1$: α_2 is weakly identified if $\sqrt{n}\alpha_1 \rightarrow h$ (as $n \rightarrow \infty$) with $h < \infty$, while α_2 is (semi-)strongly identified if $\sqrt{n}\alpha_1 \rightarrow h$ with $h = \infty$, using the terminology in AC.¹⁷ The possibility that α_2 may only be weakly identified implies that “standard” standard

¹⁷ α_2 is semi-strongly identified if, in addition, $\alpha_1 \rightarrow 0$ and strongly identified otherwise. Here, we implicitly consider (drifting) sequences of true parameters whose dependence on the sample size is omitted for notational convenience, i.e., $\alpha_1 = \alpha_{1,n}$; see, e.g., Andrews and Guggenberger (2010) for the importance of the asymptotic behavior of estimators and test statistics under drifting sequences of true parameters for determining the asymptotic size of a test.

errors may not be reliable. In this paper, we use an identification-category-selection (ICS) procedure to deal with the problem of weak identification (see, e.g., AC). In order to select an identification category (i.e., $h < \infty$ or $h = \infty$), an ICS statistic is compared to a tuning parameter, say κ , that satisfies $\kappa \rightarrow \infty$ and $\kappa/\sqrt{n} \rightarrow 0$ as $n \rightarrow \infty$, a standard choice being $\kappa = \sqrt{\ln n}$. If $\text{ICS} \leq \kappa$ one concludes that identification is weak and if $\text{ICS} > \kappa$ one concludes that identification is (semi-)strong. An ICS procedure is thus consistent if the ICS statistic is $O_p(1)$ under weak identification and diverges under (semi-)strong identification. Here, we use the standard t-statistic for testing $H_0 : \alpha_1 = 0$, say t_1 , as ICS statistic. Our ICS procedure consists in only reporting estimates of and making inferential statements about α_2 when $t_1 > \kappa$.^{18,19} In order to be conservative, we take $\kappa = 6$.²⁰

4 Data description

We apply our proposition and estimate our model using data from the five rounds of the Demographic and Health Surveys (DHS 1–5) for India (1992–93, 1998–99, 2005–06, 2015–16, and 2019–2021)²¹ and the 2002–2004 round of the District Level Household & Facility Survey (DLHS 2). The DHS and DLHS provide retrospective but precise information on the fertility (full birth history) of each woman that is between 15 and 49 years old at the time of the survey. We investigate the presence of sex-selective abortion between marriage and the birth of the third child, i.e., at birth orders 1–3. As misreporting of births has been shown to increase with the recall period (Schoumaker, 2014; Pörtner, 2022), we exclude birth intervals that started more than 15 years before the survey date. Here, birth interval refers to the time between the birth of the previous sibling (or marriage of the mother) and the birth in question. To avoid sample selection issues due to censoring, we also restrict our sample to birth intervals that started more than 5 years before the survey date. Table 1 shows the evolution of the sample size as we successively impose the aforementioned restrictions.

In order to study the evolution of sex-selective abortion patterns over time, we divide our

¹⁸Constructing tests that are valid under weak identification ($t_1 \leq \kappa$) is beyond the scope of this paper.

¹⁹From results in Ketz (2019, 2022), it can be deduced that (the confidence interval based on) the standard t-statistic for α_2 is valid under (semi-)strong identification, in that its asymptotic size does not exceed the nominal level.

²⁰We do not use $\kappa = \sqrt{\ln n}$ because we are worried that this choice might lead us to conclude that identification is (semi-)strong even though it is not, as even for our largest sample (cf. Table 2) we “only” have $\sqrt{\ln(232,935)} \approx 3.5$. The value 6 is inspired by Elliott et al. (2015) who use this number in a related context; see their running example. In unreported Monte Carlo simulations (that are available upon request), we have also found that the t-test for testing hypotheses about α_2 has good size properties under realistic choices of the parameter values that are such that t_1 is approximately normally distributed across simulations and such that less than 0.5% of the simulations have $t_1 > 6$.

²¹DHS 1–4 were downloaded from IPUMS DHS (Boyle et al., 2022) and DHS 5 from the DHS website.

Table 1: Sample description

Data source	Survey year	# women ¹	# births at birth orders 1–3				
			Total ²	5–15 years ³	Spacing ⁴	Our sample ⁵	in%
DHS 1	1992–93	78,287	113,273	48,293	48,241	12,181	10.75
DHS 2	1998–99	79,759	192,660	76,385	68,355	62,698	32.54
DLHS 2	2002–04	500,767	609,146	293,345	292,913	292,913	48.09
DHS 3	2005–06	83,342	193,893	75,091	71,177	71,177	36.71
DHS 4	2015–16	469,881	1,022,017	377,914	369,638	369,638	36.17
DHS 5	2019–21	494,019	1,073,352	384,408	376,444	370,749	34.54
Total		1,706,055	3,204,341	1,255,436	1,226,768	1,179,356	36.80

¹ We exclude women who had twins.

² We only keep births with complete information on sex, sex of previous sibling, and spacing.

³ We only keep birth intervals that started between 5 and 15 years before the survey date.

⁴ We only keep birth intervals that are between 9 months and 10 years and 9 months.

⁵ We only keep birth intervals that started in or after 1985 to 2014.

(total) sample into three 10-year periods, 1985–1994, 1995–2004, and 2005–2014,²² where the first period is pre-ban, with low availability of ultrasounds, and the last two periods are post-ban, with high availability of ultrasounds; see Section 2 for more details.

5 Empirical analysis

5.1 Results based on Proposition 1

First, we take Proposition 1 to the data to explore what can be learned from differences in average spacing about the presence of (repeated) sex-selective abortion in different groups over time.²³ To define our groups of interest, we rely on the existing literature that has identified different sex-selective abortion patterns across education levels and geographical locations (Bhalotra and Cochrane, 2010; Saikia et al., 2021; Pörtner, 2022). In particular, we consider literate and illiterate women, women living in urban and rural areas, and women living in the north and south of India.²⁴

²²The years refer to the start of the birth interval.

²³Here, we use the term “average” because we are considering the estimator, or sample analogue, of the (population) mean.

²⁴The north of India is defined as the collection of the following States: Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Ladakh, Punjab, Rajasthan, Uttarakhand, Uttar Pradesh, Bihar, Jharkhand, Madhya Pradesh, West Bengal, Gujarat. The remaining states make up the south of India.

Table 2: Proportions of male births and differences in average spacing

	Pooled	By education		By urban-rural status		By region	
		Illiterate	Literate	Rural	Urban	South	North
Birth order 1							
[1985–1994] PMB	0.513 (0.003)	0.509 (0.004)	0.517 (0.004)	0.511 (0.004)	0.518 (0.005)	0.509 (0.004)	0.517 (0.004)
DAS	0.10 (0.23)	0.13 (0.34)	-0.01 (0.30)	-0.05 (0.29)	0.30 (0.37)	0.50 (0.31)	-0.19 (0.32)
<i>n</i>	[28,602]	[14,009]	[14,564]	[18,673]	[9,929]	[13,288]	[15,314]
[1995–2004] PMB	0.515 (0.002)	0.510 (0.003)	0.517 (0.002)*	0.513 (0.002)	0.519 (0.003)*	0.514 (0.003)	0.515 (0.002)
DAS	0.17 (0.14)	0.44 (0.25)*	-0.02 (0.16)	0.28 (0.17)*	-0.12 (0.23)	-0.33 (0.20)*	0.52 (0.19)***
<i>n</i>	[75,806]	[27,459]	[48,170]	[51,532]	[24,274]	[30,558]	[45,248]
[2005–2014] PMB	0.519 (0.001)***	0.519 (0.002)***	0.520 (0.001)***	0.517 (0.001)***	0.526 (0.002)***	0.517 (0.002)***	0.521 (0.001)***
DAS	0.05 (0.07)	0.03 (0.14)	0.06 (0.08)	0.01 (0.08)	0.13 (0.13)	-0.05 (0.10)	0.15 (0.10)
<i>n</i>	[232,935]	[65,206]	[167,353]	[172,778]	[60,157]	[95,094]	[137,841]
Birth order 2 - G							
[1985–1994] PMB	0.527 (0.002)***	0.519 (0.002)**	0.535 (0.003)***	0.523 (0.002)***	0.534 (0.003)***	0.520 (0.003)***	0.531 (0.002)***
DAS	-0.41 (0.13)***	-0.28 (0.17)*	-0.46 (0.20)**	-0.32 (0.15)**	-0.54 (0.25)**	-0.13 (0.21)	-0.67 (0.16)***
<i>n</i>	[77,934]	[40,349]	[37,553]	[53,029]	[24,905]	[33,157]	[44,777]
[1995–2004] PMB	0.532 (0.002)***	0.517 (0.003)	0.544 (0.003)***	0.527 (0.002)***	0.544 (0.004)***	0.525 (0.003)***	0.537 (0.003)***
DAS	-0.36 (0.14)**	-0.63 (0.19)***	0.04 (0.20)	-0.34 (0.16)**	-0.26 (0.28)	0.08 (0.23)	-0.73 (0.18)***
<i>n</i>	[65,967]	[28,854]	[36,994]	[46,004]	[19,963]	[27,072]	[38,895]
[2005–2014] PMB	0.538 (0.002)***	0.522 (0.003)***	0.546 (0.002)***	0.533 (0.002)***	0.551 (0.003)***	0.532 (0.002)***	0.541 (0.002)***
DAS	0.02 (0.12)	0.06 (0.18)	0.16 (0.15)	0.03 (0.13)	0.20 (0.26)	0.27 (0.20)	-0.21 (0.14)
<i>n</i>	[109,392]	[37,608]	[71,582]	[83,369]	[26,023]	[43,434]	[65,958]
Birth order 3 - GG							
[1985–1994] PMB	0.539 (0.003)***	0.520 (0.004)*	0.568 (0.004)***	0.532 (0.003)***	0.557 (0.005)***	0.531 (0.004)***	0.545 (0.004)***
DAS	-1.15 (0.20)***	-0.36 (0.23)	-1.89 (0.35)***	-0.79 (0.22)***	-1.83 (0.42)***	-0.50 (0.33)	-1.63 (0.25)***
<i>n</i>	[31,258]	[18,525]	[12,721]	[22,162]	[9,096]	[12,410]	[18,848]
[1995–2004] PMB	0.550 (0.003)***	0.529 (0.004)***	0.575 (0.005)***	0.539 (0.004)***	0.581 (0.006)***	0.540 (0.005)***	0.555 (0.004)***
DAS	-1.27 (0.23)***	-0.75 (0.29)***	-1.42 (0.37)***	-0.89 (0.26)***	-1.95 (0.51)***	-0.47 (0.40)	-1.78 (0.28)***
<i>n</i>	[24,807]	[13,383]	[11,383]	[18,266]	[6,541]	[9,030]	[15,777]
[2005–2014] PMB	0.561 (0.003)***	0.533 (0.004)***	0.587 (0.003)***	0.556 (0.003)***	0.585 (0.006)***	0.556 (0.004)***	0.564 (0.003)***
DAS	-0.98 (0.20)***	-0.63 (0.26)**	-0.75 (0.29)***	-0.85 (0.21)***	-1.10 (0.50)**	-0.30 (0.35)	-1.36 (0.23)***
<i>n</i>	[38,418]	[17,768]	[20,575]	[31,040]	[7,378]	[12,917]	[25,501]

The table shows the proportions of male births (PMB) and the differences in average spacing between boys and girls (DAS) for different samples: G and GG denote “first child is a girl” and “first two children are girls”, respectively. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (p -values are for two-sided t -tests for testing that the probability of male birth equals π and that the difference in mean spacing equals 0).

Table 2 reports the proportions of male births (PMB) along with the differences in average spacing between boys and girls (DAS) for our different groups by period, birth order, and siblings composition.²⁵ For birth order 1, PMB and DAS largely agree in terms of evidence of sex-selective abortion. For most groups in the first two periods, PMB is not significantly different from the natural probability of male birth, π , which we take equal to 0.513 (cf. Chao et al., 2019; Dubuc and Coleman, 2007),²⁶ and DAS is not significantly different from zero. In the last period, PMB suggests the presence of sex-selective abortion, in line with the findings in Saikia et al. (2021). DAS, however, does not provide any further evidence of sex-selective abortion in the last period. For birth orders 2 and 3 with “only girls” sibling compositions, PMB provides evidence of sex-selective abortion for almost all periods and all groups, being more imbalanced at birth order 3. DAS complements this picture by showing some evidence of *repeated* sex-selective abortion at birth order 2, in the first two periods, and strong evidence of *repeated* sex-selective abortion at birth order 3, being statistically different from zero and negative for many periods and groups.

5.2 Estimation results

In order to obtain further insights on the prevalence of sex-selective abortion, we now estimate our model. Estimation is performed over the samples with the largest proportions of male births, i.e., at birth orders 2 and 3 when all previous children are girls (cf. Tables 2 and C.1 in Appendix C).

5.2.1 Share of women that abort

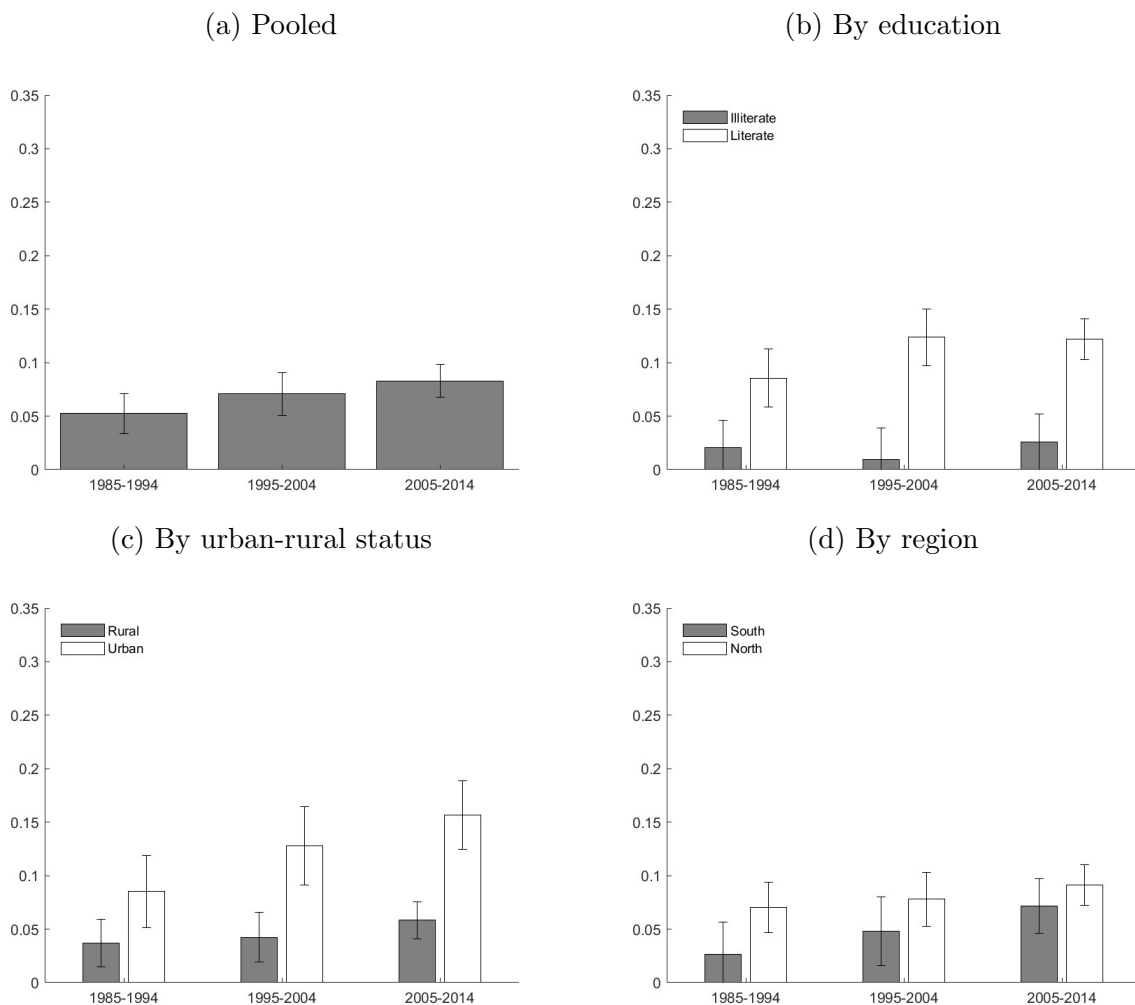
We first report our estimates of the shares of women that abort (when pregnant with a female foetus), $\hat{\alpha}_1$. Figure 3 reports the corresponding estimates at birth order 2 when the first-born is a girl and Figure 4 at birth order 3 when the first two children are girls. Both figures also show 95% confidence intervals for α_1 , while the t-statistics for testing $H_0 : \alpha_1 = 0$, t_1 , that serve as our ICS statistics are reported in Table C.2 in Appendix C. We note, however, that the reported confidence intervals have to be taken with a grain of salt, particularly for small values of t_1 , as they do not take into account that α_2 may only be weakly identified.²⁷

²⁵In the interest of space, Table 2 only reports these statistics for the “only girls” sibling compositions. The statistics for the remaining sibling compositions are reported in Table C.1 in Appendix C.

²⁶The standard error for PMB is computed as $\sqrt{\text{PMB}(1 - \text{PMB})/n}$.

²⁷The underlying standard errors are based on a numerical approximation of the second-order derivative matrix of $\sum_{i=1}^n \log L(\theta; t_i, y_i)$ evaluated at $\hat{\theta}$. This numerical approximation becomes unreliable or even infeasible when $\hat{\alpha}_1$ is (very) close to zero. That said, we were able to compute it for all estimation results reported in Figures 3 and 4 (using the DERIVESTsuite package for Matlab).

Figure 3: Shares of women that abort at birth order 2 when the first-born is a girl

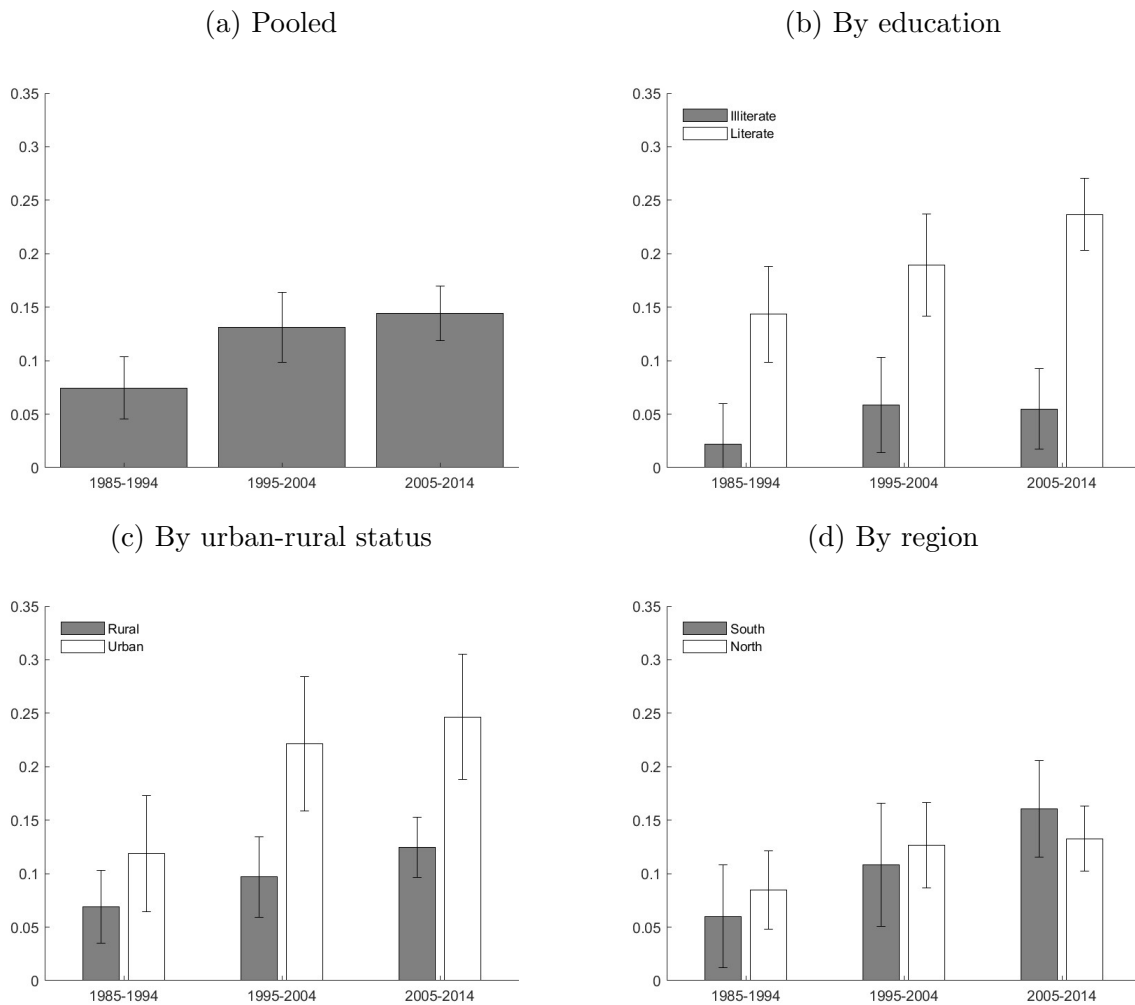


Note: Each panel shows the estimated shares of women that abort when pregnant with a female foetus, $\hat{\alpha}_1$, together with 95% confidence intervals for the three time periods.

Panel (a) of Figure 3 shows that the share of women that abort at birth order 2 slowly increases over time from $\sim 5\%$ in the first period to $\sim 8\%$ in the last period. Panels (b)–(d) show that these estimates hide stark heterogeneity across socio-demographic/geographical groups. In particular, the decomposition reveals that literate women and women in urban areas are much more likely to abort than illiterate women and women in rural areas, respectively. While the share of women that abort among illiterate women remains small and relatively constant over time, there is a small increase in the share of women that abort among rural women, which reaches $\sim 6\%$ in the last period compared to $\sim 16\%$ among urban women. While women in the north are estimated to be more likely to abort than women in the south, the estimates are relatively close.

At birth order 3, the picture is qualitatively similar, but with higher shares of women

Figure 4: Shares of women that abort at birth order 3 when the first two children are girls



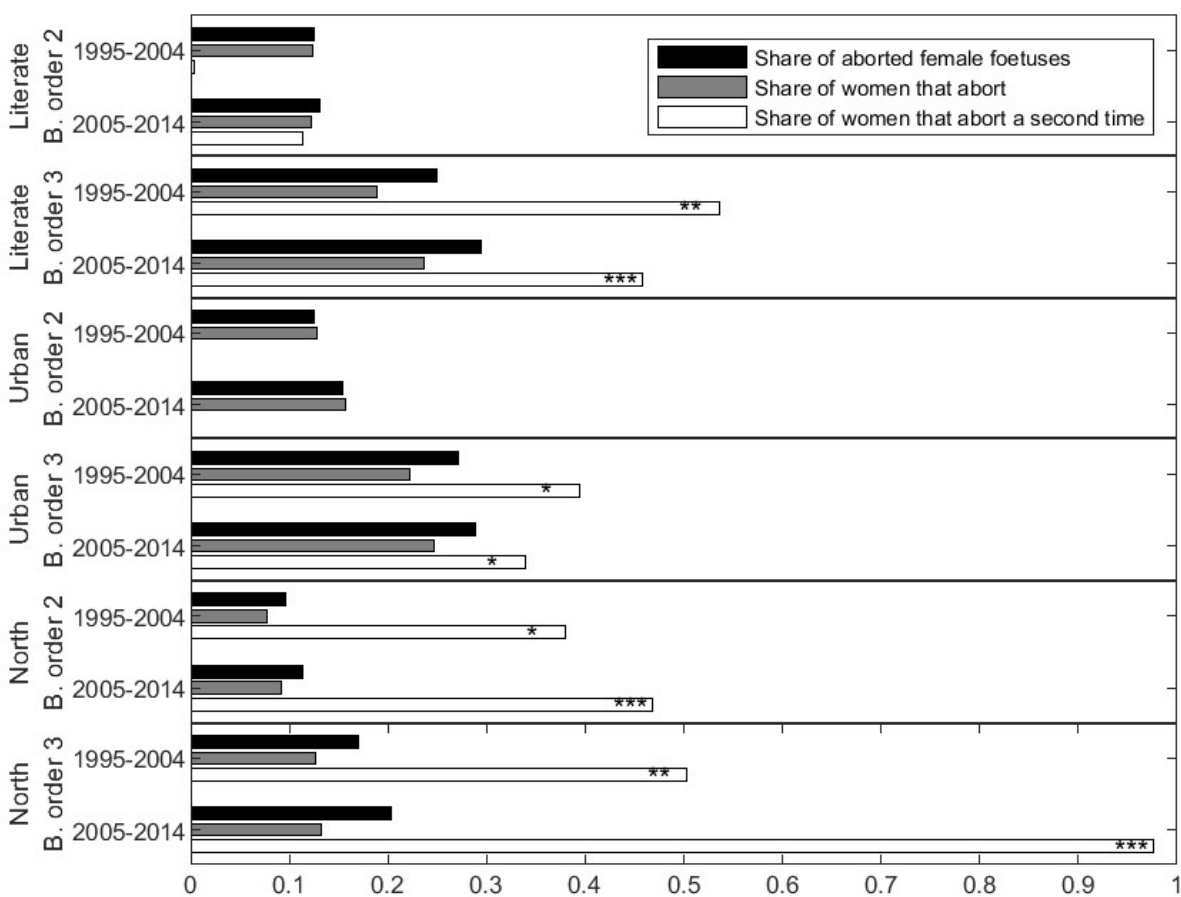
Note: Each panel shows the estimated shares of women that abort when pregnant with a female foetus, $\hat{\alpha}_1$, together with 95% confidence intervals for the three time periods.

that abort, cf. Figure 4. Similar to above, there is an increase in the share of women that abort over time, from $\sim 7\%$ in the first period to $\sim 14\%$ in the last period, which may in part be due to the increased availability of ultrasounds. Again, the decomposition by socio-demographic/geographical groups uncovers large heterogeneity. Literate women and women in urban areas are more likely to abort and, in both groups, the share of women that abort has increased by more than 9 percentage points from the first to the last period, from $\sim 0.14\%$ ($\sim 0.12\%$) to $\sim 0.23\%$ (0.25%) for literate women (women in urban areas). As above, there is little difference in the share of women that abort between women in the north and women in the south.

5.2.2 Share of women that abort a second time

Next, we report our estimates of the shares of women that abort a second time (when again pregnant with a female foetus after a first abortion), $\hat{\alpha}_2$. As discussed in Section 3.4, we only consider samples for which $t_1 > 6$. In particular, we focus on literate women, woman in urban areas, and women in the north in the last two periods, for which $t_1 > 6$ at birth orders 2 and 3, cf. Table C.2. The results are graphically depicted in Figure 5; Table C.3 in Appendix C provides a tabulated version of the results that includes standard errors.

Figure 5: Shares of aborted female foetuses, shares of women that abort, and shares of women that abort a second time for selected samples



Note: The figure shows the estimated shares of aborted female foetuses, the estimated shares of women that abort, $\hat{\alpha}_1$, and the estimated shares of women that abort a second time, $\hat{\alpha}_2$, for selected samples (with “only girls” sibling compositions). “Significance” is only indicated for $\hat{\alpha}_2$: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (p -values are for the one-sided t-test, i.e., $H_0 : \alpha_2 = 0$ vs. $H_1 : \alpha_2 > 0$).

For each sample, Figure 5 shows three quantities: the estimated shares of aborted female

foetuses (black bar),²⁸ the estimated shares of women that abort, $\hat{\alpha}_1$, already reported in Figures 3 and 4 (gray bar), and the estimated shares of women that abort a second time, $\hat{\alpha}_2$ (white bar). The first striking result is that at birth order 2, women in some groups do not abort a second time or, put differently, there is no repeated sex-selective abortion, i.e., $\hat{\alpha}_2 \approx 0$. This is the case for literate women and women in urban areas and provides evidence against the assumption, sometimes made in the literature, that women abort indefinitely until they have a boy (see, e.g., Guilмото et al., 2020). We note that whenever $\hat{\alpha}_2 \approx 0$, the estimated share of aborted female foetuses is (essentially) equal to the estimated share of women that abort. This is in line with the model: If women abort at most once, then the share of women that abort *when pregnant with a female foetus* must be equal to the share of aborted female foetuses. Second, we find strong evidence of repeated sex-selective abortion at birth order 3 for all groups, i.e., literate women, urban women, and women in the north. For both periods, the estimated shares of women that abort a second time are large and significantly different from zero at the 10% significance level. While the estimates suggest that the shares of women that abort a second time have been stable over time for literate and urban women, there seems to be an increase for women in the north. Finally, we note that a positive share of women that abort a second time implies that the share of women that abort is less than the share of aborted female foetuses. As before, this is in line with the model. In case of large estimates of α_2 , as in the last period for women in the north, the difference can be quite important, with the share (number) of aborted female foetuses being 50% larger than the share (number) of women that abort.²⁹ This result underlines the relevance of measuring the number of women that abort, on top of the number of aborted female foetuses.

6 Conclusion

Measuring how many women sex-selectively abort and whether they do so repeatedly is not feasible using administrative or self-reported survey data. We propose an innovative methodology that exploits information in spacing to measure the share of women that abort, and the share of women that abort repeatedly, between two consecutive births. In an application using Indian data, we find important heterogeneity across socio-demographic/geographic

²⁸The estimated share of aborted female foetuses or, equivalently, the estimated share of missing female births is given by $\frac{\text{PMB} - \pi}{(1 - \pi)\pi}$ and equals the number of missing female births ($n \times \text{PMB} \frac{1 - \pi}{\pi} - n(1 - \text{PMB})$), according to “Sen’s original method”, divided by the number of expected female births ($n(1 - \pi)$) (cf. equations (2) and (3) in Guilмото et al., 2020, where $\text{OMB} = n \times \text{PMB}$, $\text{ESRB} = \frac{\pi}{1 - \pi}$, and $\text{OFB} = n(1 - \text{PMB})$).

²⁹We can use the terms “share” and “number” interchangeably here, because the two “shares” have the same denominator, $n(1 - \pi)$, such they cancel out when we take the ratio.

groups, birth orders, and siblings composition. In some samples, such as women in the north at birth order 3 whose first two children are girls, the share of aborted female fetuses is estimated to be 50% larger than the share of women that abort. This highlights that our proposed measure of the prevalence of sex-selective abortion is empirically relevant.

Our proposed measure should also be useful for policy makers. If repeated sex-selective abortion is indicative of a higher utility of having a boy net of costs, our methodology can be used to identify populations with different net utilities. This, in turn, can be useful for targeting. For example, a population with a higher net utility of having a boy may require larger incentives, e.g., larger cash transfers, to refrain from performing sex-selective abortions.

Our methodology only requires information on women’s birth histories (i.e., sex and dates of birth of the children), which can be an advantage or disadvantage. This information is largely available in low and middle-income countries, where large household surveys are regularly conducted. Therefore, our methodology should prove useful for studying sex-selective abortion patterns in such countries. However, our methodology cannot be applied in countries where such information is not available. Another disadvantage of our methodology is that it requires large sample sizes (to overcome possible weak identification issues; see Sections 3.4 and 5.2.2), such that it may not be suitable for the study of sex-selective abortion patterns in countries with small populations.

Lastly, this paper makes several assumptions that could be restrictive. For example, we currently assume that there is no correlation between how long women, or households, wait before trying to conceive and their willingness to abort if pregnant with a female foetus. Relaxing this kind of assumption is left for further research.

References

- Alesina, Alberto, Paola Giuliano, and Nathan Nunn**, “Traditional agricultural practices and the sex ratio today,” *PloS one*, 2018, *13* (1), e0190510.
- Anderson, Siwan and Debraj Ray**, “Missing Women: Age and Disease,” *The Review of Economic Studies*, 2010, *77* (4), 1262–1300.
- Andrews, Donald W. K. and Patrik Guggenberger**, “Asymptotic Size and a Problem With Subsampling and With the m out of n Bootstrap,” *Econometric Theory*, 2010, *26* (2), 426–468.
- **and Xu Cheng**, “Estimation and Inference With Weak, Semi-Strong, and Strong Identification,” *Econometrica*, 2012, *80* (5), 2153–2211.

- Anukriti, Sharma, Sonia Bhalotra, and Eddy H. F. Tam**, “On the quantity and quality of girls: Fertility, parental investments and mortality,” *The Economic Journal*, 2022, *132* (641), 1–36.
- Baland, Jean-Marie, Guilhem Cassan, and Francois Woitrin**, “Sex-Selective Abortions and Instrumental Births as the two faces of the Stopping Rule. New measures and world evidence,” *Working Paper*, 2022.
- Bhalotra, Sonia R. and Tom Cochrane**, “Where have all the young girls gone? Identification of sex selection in India,” *IZA Discussion Paper*, 2010.
- Bongaarts, John and Christophe Z. Guilmoto**, “How Many More Missing Women? Excess Female Mortality and Prenatal Sex Selection, 1970–2050,” *Population and Development Review*, 2015, *41* (2), 241–269.
- Boyle, Elizabeth Heger, Miriam King, and Matthew Sobek**, “IPUMS-Demographic and Health Surveys: Version 9 [dataset],” *IPUMS and ICF*, 2022.
- Chandra, Aparna, Mrinal Satish, Shreya Shree, and Mini Saxena**, “Legal barriers to accessing safe abortion services in India: A fact finding study,” National Law School of India University, Bengaluru 2021.
- Chao, Fengqing, Patrick Gerland, Alex R. Cook, and Leontine Alkema**, “Systematic assessment of the sex ratio at birth for all countries and estimation of national imbalances and regional reference levels,” *Proceedings of the National Academy of Sciences*, 2019, *116* (19), 9303–9311.
- Dahl, Gordon B. and Enrico Moretti**, “The Demand for Sons,” *The Review of Economic Studies*, 2008, *75* (4), 1085–1120.
- Diamond-Smith, Nadia and David Bishai**, “Evidence of self-correction of child sex ratios in India: a district-level analysis of child sex ratios from 1981 to 2011,” *Demography*, 2015, *52* (2), 641–666.
- Dubuc, Sylvie and David Coleman**, “An increase in the sex ratio of births to India-born mothers in England and Wales: evidence for sex-selective abortion,” *Population and Development Review*, 2007, *33* (2), 383–400.
- Elliott, Graham, Ulrich K. Müller, and Mark W. Watson**, “Nearly Optimal Tests When a Nuisance Parameter Is Present under the Null Hypothesis,” *Econometrica*, 2015, *83*, 771–811.

- Goli, Srinivas, Astghik Mavisakalyan, Anu Rammohan, and Loan Vu**, “Conflicts and son preference: Micro-level evidence from 58 countries,” *Economics & Human Biology*, 2022, *46*, 101146.
- Grimes, David A., Janie Benson, Susheela Singh, Mariana Romero, Bela Ganatra, Friday E. Okonofua, and Iqbal H. Shah**, “Unsafe abortion: the preventable pandemic,” *Lancet (London, England)*, November 2006, *368* (9550), 1908–1919.
- Guilmoto, Christophe Z.**, “Sex Imbalances at Birth: Current trends, consequences and policy implications,” *UNFPA Asia and Pacific Regional Office*, 2012.
- , **Fengqing Chao, and Purushottam M. Kulkarni**, “On the estimation of female births missing due to prenatal sex selection,” *Population Studies*, 2020, *74* (2), 283–289. PMID: 32489140.
- Heath, Rachel and Xu Tan**, “Worth fighting for: Daughters improve their mothers’ autonomy in South Asia,” *Journal of Development Economics*, 2018, *135*, 255–271.
- Hwang, Jisoo, Chulhee Lee, and Esther Lee**, “Gender norms and housework time allocation among dual-earner couples,” *Labour Economics*, 2019, *57*, 102–116.
- Jayachandran, Seema**, “Fertility decline and missing women,” *American Economic Journal: Applied Economics*, 2017, *9* (1), 118–39.
- Jha, Prabhat, Maya A. Kesler, Rajesh Kumar, Faujdar Ram, Usha Ram, Lukasz Aleksandrowicz, Diego G. Bassani, Shailaja Chandra, and Jayant K. Banthia**, “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*, 2011, *377* (9781), 1921–1928.
- Ketz, Philipp**, “On asymptotic size distortions in the random coefficients logit model,” *Journal of Econometrics*, 2019, *212* (2), 413–432.
- , “Allowing for weak identification when testing GARCH-X type models,” 2022. arXiv:2210.11398.
- Klasen, Stephan and Claudia Wink**, ““Missing women”: Revisiting the debate,” *Feminist Economics*, 2003, *9* (2–3), 263–299.
- Kumar, Sneha and Nistha Sinha**, “Preventing more missing girls: A review of policies to tackle son preference,” *The World Bank Research Observer*, 2020, *35* (1), 87–121.

- Mavisakalyan, Astghik and Anna Minasyan**, “The role of conflict in sex discrimination: The case of missing girls,” *Economic development and cultural change*, 2023, 71 (2), 443–484.
- Milazzo, Annamaria**, “Why are adult women missing? Son preference and maternal survival in India,” *Journal of Development Economics*, 2018, 134, 467–484.
- Moschopoulos, Peter G.**, “The distribution of the sum of independent gamma random variables,” *Annals of the Institute of Statistical Mathematics*, 1985, 37 (3), 541–544.
- Orzack, Steven H., J. William Stubblefield, Viatcheslav R. Akmaev, Pere Colls, Santiago Munné, Thomas Scholl, David Steinsaltz, and James E. Zuckerman**, “The human sex ratio from conception to birth,” *Proceedings of the National Academy of Sciences*, 2015, 112 (16), E2102–E2111.
- Oster, Emily**, “How Long Does It Take to Get Pregnant?,” 2022. Retrieved from “<https://www.parentdata.org/p/how-long-does-it-take-to-get-pregnant>” on December 13, 2022.
- Pörtner, Claus C.**, “Birth Spacing and Fertility in the Presence of Son Preference and Sex-Selective Abortions: India’s Experience Over Four Decades,” *Demography*, 2022, 59 (1), 61–88.
- Qian, Nancy**, “Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance,” *The Quarterly Journal of Economics*, 2008, 123 (3), 1251–1285.
- Rastogi, Garima and Anisha Sharma**, “Unwanted daughters: the unintended consequences of a ban on sex-selective abortions on the educational attainment of women,” *Journal of Population Economics*, 2022, pp. 1–44.
- Saikia, Nandita, Catherine Meh, Usha Ram, Jayanta Kumar Bora, Bhaskar Mishra, Shailaja Chandra, and Prabhat Jha**, “Trends in missing females at birth in India from 1981 to 2016: analyses of 2·1 million birth histories in nationally representative surveys,” *The Lancet Global Health*, 2021, 9 (6), e813–e821.
- Schoumaker, Bruno**, *Quality and consistency of DHS fertility estimates, 1990 to 2012*, ICF International Rockville, Maryland, 2014.
- Sen, Amartya**, “Women’s survival as a development problem,” *Bulletin of the American Academy of Arts and Sciences*, 1989, 43 (2), 14–29.

Stillman, Melissa, Jennifer J. Frost, Susheela Singh, Ann M. Moore, and Shveta Kalyanwala, “Abortion in India: a literature review,” *New York: Guttmacher Institute*, 2014, pp. 12–14.

World Health Organization, “Abortion care guideline,” 2022.

A Proof and “extension” of Proposition 1

Proof of Proposition 1. To prove (i), note that $T_b = T_b^0$ if $N = 0$. Therefore, if $N = 0$, T_b is independent of Y such that $E(T_b|Y = 0) = E(T_b) = E(T_b|Y = 1)$ and the results follows.

To prove (ii), note that $E(T_b|Y = 0) > E(T_b|Y = 1)$ if $N = 1$. This together with (i) yields the desired result. To see that $E(T_b|Y = 0) > E(T_b|Y = 1)$ if $N = 1$, note that

$$E(T_b|Y = y) = E(T_b^1)P(A = 1|Y = y) + E(T_b^0)(1 - P(A = 1|Y = y))$$

for $y \in \{0, 1\}$. The result then follows by noting that $E(T_b^1) > E(T_b^0)$, since $T_s > 0$ and $T_c \geq 0$, and $P(A = 1|Y = 0) > P(A = 1|Y = 1)$, cf. equations (1) and (2). \square

Next, we show that Proposition 1(ii) continues to hold, under the condition stated in the main text, when we allow T_w to depend on whether a household aborts (or would abort) if pregnant with a female foetus (for the first time between two births). Let $W \in \{0, 1\}$ denote whether a household aborts if pregnant with a female foetus ($W = 1$) or not ($W = 0$). With this extension of the model, we have $P(A = 1, W = 1|Y = y) = P(A = 1|Y = y)$ (as $A = 1 \Rightarrow W = 1$), $P(A = 1, W = 0|Y = y) = 0$ (as $W = 0 \Rightarrow A = 0$), $P(A = 0, W = 0|Y = 0) = P(A = 0|Y = 0) = 1 - P(A = 1|Y = 0)$ (as $\{A = 0\} \cap \{Y = 0\} \Rightarrow W = 0$), $P(A = 0, W = 1|Y = 1) = \frac{\alpha_1}{(1-p)^{\alpha_1+1}}$, and $P(A = 0, W = 0|Y = 1) = \frac{1-\alpha_1}{(1-p)^{\alpha_1+1}}$ for $y \in \{0, 1\}$. In order to allow T_w to depend on W , let $T_w = T_w^W = WT_w^1 + (1 - W)T_w^0$, where T_w^1 (T_w^0) denotes the *waiting time* for a household that aborts (does not abort) if pregnant with a female foetus. Let

$$T_b \equiv T_b^{A,W} = T_w^W + T_c + A(T_c + T_s) + T_p$$

for $A, W \in \{0, 1\}$. Then, the desired result follows as

$$\begin{aligned} E(T_b|Y = 1) &= E(T_b^{1,1})P(A = 1|Y = 1) + E(T_b^{0,1})P(A = 0, W = 1|Y = 1) \\ &\quad + E(T_b^{0,0})P(A = 0, W = 0|Y = 1) \\ &\leq E(T_b^{1,1})P(A = 1|Y = 1) + E(T_b^{0,0})(1 - P(A = 1|Y = 1)) \\ &< E(T_b^{1,1})P(A = 1|Y = 0) + E(T_b^{0,0})(1 - P(A = 1|Y = 0)) = E(T_b|Y = 0), \end{aligned}$$

where the first (weak) inequality holds by assumption, namely $E(T_w^1) \leq E(T_w^0)$ and the second inequality by the same argument used in proving part (ii) of Proposition 1, with $T_b^{1,1}$ ($T_b^{0,0}$) replacing T_b^1 (T_b^0).

B Estimation details

B.1 Definition of $f_{T_b^a}(\cdot)$

First, we define $f_\Gamma(\cdot)$ for sake of completeness. In particular,

$$f_\Gamma(t; \gamma, \beta) = \begin{cases} \frac{t^{\gamma-1} e^{-\frac{t}{\beta}}}{\beta^\gamma \Gamma(\gamma)} & \text{if } t > 0 \\ 0 & \text{otherwise} \end{cases},$$

where $\Gamma(\cdot)$ denotes the gamma function. Next, we define $f_{\Sigma\Gamma}(\cdot)$. To that end, assume without loss of generality that $\beta_1 < \beta_2$. Then,

$$f_{\Sigma\Gamma}(t; \gamma_1, \beta_1, \gamma_2, \beta_2) = \begin{cases} C \sum_{k=0}^{\infty} \delta_k \frac{t^{\gamma_1+\gamma_2+k-1} e^{-\frac{t}{\beta_1}}}{\beta_1^{\gamma_1+\gamma_2+k} \Gamma(\gamma_1+\gamma_2+k)} & \text{if } t > 0 \\ 0 & \text{otherwise,} \end{cases}$$

where $C = \left(\frac{\beta_1}{\beta_2}\right)^{\gamma_2}$ and where δ_k is defined recursively by

$$\delta_{k+1} = \frac{\gamma_2}{k+1} \sum_{i=1}^{k+1} \left(1 - \frac{\beta_1}{\beta_2}\right)^i \delta_{k+1-i}$$

for $k = 0, 1, 2, \dots$ with $\delta_0 = 1$; see Moschopoulos (1985) for more details. To numerically evaluate the infinite series in $f_{\Sigma\Gamma}(\cdot)$, we rely on a finite series approximation. In particular, we truncate the series at 30 terms. The resulting approximation error is immaterial.

Lastly, we note that $f_{T_b^a}(\cdot)$ uses the fact that the sum of two independent gamma-distributed random variables with the same scale parameter, say β , but (possibly) different shape parameters, say γ_1 and γ_2 , is gamma-distributed with shape parameter $\gamma_1 + \gamma_2$ and scale parameter β .

B.2 Calibration of γ_c and β_c

The calibration of γ_c and β_c is performed by means of maximum likelihood, fitting a gamma distribution to the time between marriage and first birth (minus 9); it is performed for each

of our three time periods separately.³⁰ The underlying assumptions are that households try to conceive immediately after marriage, such that the time between marriage and first birth (minus 9) is a good proxy for the time it takes to conceive, and that there is no sex-selective abortion before the birth of the first child. The second assumption is largely corroborated by the numbers in Table 2 and widely accepted in the literature (see, e.g., Dahl and Moretti, 2008; Milazzo, 2018; Heath and Tan, 2018).

C Additional tables

³⁰Here, we only use DHS 4 because it is the only round that differentiates between date of marriage and date of marriage contract.

Table C.1: Proportions of male births and differences in average spacing for remaining sibling compositions

	Pooled	By education		By urban-rural status		By region	
		Illiterate	Literate	Rural	Urban	South	North
Birth order 2 - B							
[1985–1994] PMB	0.520 (0.002)***	0.525 (0.002)***	0.515 (0.003)	0.522 (0.002)***	0.517 (0.003)	0.519 (0.003)**	0.522 (0.002)***
DAS	0.37 (0.13)***	0.58 (0.17)***	0.08 (0.20)	0.39 (0.15)***	0.30 (0.25)	0.42 (0.20)**	0.33 (0.16)**
<i>n</i>	[82,748]	[43,361]	[39,354]	[56,480]	[26,268]	[35,163]	[47,585]
[1995–2004] PMB	0.508 (0.002)**	0.510 (0.003)	0.507 (0.003)**	0.510 (0.002)	0.504 (0.003)**	0.507 (0.003)*	0.509 (0.002)
DAS	0.19 (0.14)	0.25 (0.20)	0.12 (0.20)	0.31 (0.16)*	-0.12 (0.28)	0.23 (0.23)	0.16 (0.18)
<i>n</i>	[68,287]	[30,125]	[38,053]	[47,656]	[20,631]	[27,809]	[40,478]
[2005–2014] PMB	0.501 (0.001)***	0.509 (0.003)*	0.497 (0.002)***	0.502 (0.002)***	0.500 (0.003)***	0.498 (0.002)***	0.503 (0.002)***
DAS	0.20 (0.12)*	0.46 (0.17)***	-0.02 (0.15)	0.24 (0.13)*	0.07 (0.26)	-0.13 (0.19)	0.39 (0.14)***
<i>n</i>	[111,423]	[39,591]	[71,636]	[84,601]	[26,822]	[44,676]	[66,747]
Birth order 3 - GB							
[1985–1994] PMB	0.527 (0.003)***	0.532 (0.004)***	0.520 (0.005)	0.528 (0.003)***	0.527 (0.006)**	0.519 (0.005)	0.532 (0.004)***
DAS	0.52 (0.20)**	0.62 (0.24)**	0.28 (0.36)	0.76 (0.23)***	-0.10 (0.42)	0.51 (0.35)	0.50 (0.25)**
<i>n</i>	[29,363]	[18,409]	[10,940]	[21,349]	[8,014]	[10,962]	[18,401]
[1995–2004] PMB	0.526 (0.003)***	0.519 (0.004)	0.535 (0.005)***	0.527 (0.004)***	0.522 (0.007)	0.526 (0.006)**	0.525 (0.004)***
DAS	0.41 (0.24)*	0.45 (0.29)	0.47 (0.40)	0.38 (0.27)	0.46 (0.51)	0.39 (0.43)	0.42 (0.28)
<i>n</i>	[21,593]	[12,771]	[8,779]	[16,336]	[5,257]	[7,248]	[14,345]
[2005–2014] PMB	0.526 (0.003)***	0.528 (0.004)***	0.524 (0.004)**	0.526 (0.003)***	0.528 (0.007)**	0.518 (0.005)	0.530 (0.004)***
DAS	0.41 (0.22)*	0.56 (0.29)**	0.18 (0.34)	0.46 (0.24)*	0.16 (0.58)	0.39 (0.41)	0.37 (0.26)
<i>n</i>	[28,402]	[15,228]	[13,118]	[23,212]	[5,190]	[9,267]	[19,135]
Birth order 3 - BG							
[1985–1994] PMB	0.516 (0.003)	0.512 (0.004)	0.523 (0.005)**	0.512 (0.003)	0.527 (0.006)**	0.505 (0.005)*	0.523 (0.004)***
DAS	-0.51 (0.20)**	-0.40 (0.24)*	-0.65 (0.36)*	-0.62 (0.23)***	-0.16 (0.42)	-0.41 (0.35)	-0.64 (0.25)**
<i>n</i>	[28,882]	[18,046]	[10,826]	[20,877]	[8,005]	[10,959]	[17,923]
[1995–2004] PMB	0.521 (0.003)**	0.519 (0.004)	0.524 (0.005)**	0.520 (0.004)*	0.522 (0.007)	0.515 (0.006)	0.524 (0.004)**
DAS	-0.68 (0.24)***	-0.86 (0.29)***	-0.43 (0.40)	-0.70 (0.27)***	-0.62 (0.52)	-0.64 (0.43)	-0.73 (0.28)***
<i>n</i>	[21,540]	[12,886]	[8,613]	[16,250]	[5,290]	[7,399]	[14,141]
[2005–2014] PMB	0.515 (0.003)	0.510 (0.004)	0.521 (0.004)*	0.514 (0.003)	0.523 (0.007)	0.502 (0.005)**	0.522 (0.004)**
DAS	-0.09 (0.22)	-0.36 (0.28)	0.34 (0.35)	0.04 (0.24)	-0.59 (0.57)	0.41 (0.41)	-0.45 (0.26)*
<i>n</i>	[27,717]	[14,979]	[12,691]	[22,632]	[5,085]	[9,152]	[18,565]
Birth order 3 - BB							
[1985–1994] PMB	0.505 (0.003)**	0.511 (0.004)	0.495 (0.005)***	0.506 (0.003)**	0.505 (0.006)	0.495 (0.005)***	0.512 (0.004)
DAS	0.30 (0.20)	-0.03 (0.24)	0.82 (0.38)**	0.28 (0.23)	0.33 (0.42)	0.43 (0.34)	0.18 (0.26)
<i>n</i>	[28,949]	[18,832]	[10,106]	[20,952]	[7,997]	[11,415]	[17,534]
[1995–2004] PMB	0.500 (0.004)***	0.503 (0.004)**	0.496 (0.006)***	0.505 (0.004)**	0.487 (0.007)***	0.495 (0.006)***	0.503 (0.004)**
DAS	0.30 (0.25)	0.31 (0.30)	0.23 (0.42)	0.26 (0.28)	0.33 (0.51)	0.19 (0.43)	0.33 (0.30)
<i>n</i>	[20,228]	[12,356]	[7,838]	[15,124]	[5,104]	[7,356]	[12,872]
[2005–2014] PMB	0.491 (0.003)***	0.501 (0.004)***	0.478 (0.005)***	0.491 (0.004)***	0.488 (0.007)***	0.482 (0.005)***	0.495 (0.004)***
DAS	0.40 (0.24)*	0.23 (0.30)	0.41 (0.38)	0.13 (0.26)	1.52 (0.59)**	0.36 (0.43)	0.35 (0.29)
<i>n</i>	[25,105]	[13,845]	[11,213]	[20,292]	[4,813]	[8,947]	[16,158]

The table shows the proportions of male births (PMB) and the differences in average spacing between boys and girls (DAS) for different samples: B denotes “first child is a boy” and GB, BG, and BB denote “first two children are a girl and a boy, a boy and a girl, and two boys”, respectively. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (p -values are for two-sided t-tests for testing that the probability of male birth equals π and that the difference in mean spacing equals 0).

Table C.2: t-statistics for testing $H_0 : \alpha_1 = 0$ vs. $H_1 : \alpha_1 > 0$

Birth order	Period	Illiterate	Literate	Rural	Urban	South	North
2	1985–1994	1.55	6.15	3.26	4.92	1.74	5.78
	1995–2004	0.64	9.09	3.57	6.82	2.91	6.07
	2005–2014	1.94	12.57	6.60	9.54	5.48	9.37
3	1985–1994	1.16	6.27	3.96	4.30	2.44	4.56
	1995–2004	2.58	7.77	5.02	6.88	3.68	6.24
	2005–2014	2.86	13.67	8.70	8.26	6.95	8.50

Table C.3: Shares of aborted female fetuses, shares of women that abort, and shares of women that abort a second time for selected samples with standard errors

Group	Birth order	Period	Share of aborted female fetuses	Share of women that abort	Share of women that abort a second time	
Literate	2	1995–2004	0.125 (0.010)	0.124 (0.014)	0.003 (0.166)	
		2005–2014	0.130 (0.007)	0.122 (0.010)	0.113 (0.131)	
	3	1995–2004	0.249 (0.019)	0.189 (0.024)	0.536 (0.253)	
		2005–2014	0.295 (0.014)	0.237 (0.017)	0.458 (0.147)	
	Urban	2	1995–2004	0.125 (0.014)	0.128 (0.019)	0.001 (0.217)
			2005–2014	0.154 (0.012)	0.157 (0.016)	0.000 (0.168)
3		1995–2004	0.271 (0.024)	0.221 (0.032)	0.394 (0.281)	
		2005–2014	0.289 (0.023)	0.246 (0.030)	0.339 (0.242)	
North		2	1995–2004	0.097 (0.010)	0.078 (0.013)	0.380 (0.267)
			2005–2014	0.114 (0.008)	0.091 (0.010)	0.468 (0.185)
	3	1995–2004	0.170 (0.016)	0.127 (0.020)	0.503 (0.284)	
		2005–2014	0.204 (0.012)	0.133 (0.016)	0.977 (0.266)	

The table shows the estimated shares of aborted female fetuses, the estimated shares of women that abort, $\hat{\alpha}_1$, and the estimated shares of women that abort a second time, $\hat{\alpha}_2$, for selected samples (with “only girls” sibling compositions). Standard errors are reported in parentheses.