Quantitative Economics 14 (2023), 309–347 1759-7331/20230309

The demographic consequences of sex-selection technology

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Over the last several years, highly accurate methods of sex selection before conception have been developed. Given that strong preferences for sex variety in offspring have been documented for the U.S., we ask what the demographic consequences of sex-selection technology could be. Lacking variation across space and time in access to this technology, we estimate a dynamic programming model of fertility decisions with microdata on fertility histories. We leverage the quasi-experimental variation inherent in the random determination of sex to identify the key structural parameter characterizing preferences for sex variety in offspring. We then simulate the introduction of this technology. While this technology can reduce fertility by allowing parents to efficiently reach their preferred sex mix, it could also increase it. This is because without this technology, many parents may opt not to have another baby given the uncertainty about its sex. Results suggest that these two effects operate simultaneously, but on net, sex-selection technology ends up reducing the average family size among married women by less than 2% in the steady state, a much smaller decline than the one that would be predicted by alternative methods.

Keywords. Sex-selection, fertility.

JEL classification. J11, J13.

1. Introduction and motivation

In the United States, many couples keep trying until they have a child of a specific sex. It is likely that strong parental preferences for sex variety in offspring (i.e., having at least one child of each sex) drive this behavior. Many couples who would ideally have had only one boy and one girl may end up with three or even four children of the same sex before eventually giving up. In this sense, the uncertainty about sex at the time of fertilization generates excess fertility behavior in the population at large. A less overt, a more

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We thank Jerome Adda, S. Anukriti, Alejandro Badel, Kelly Bishop, Meta Brown, Greg Caetano, Jesus Carro, Maria Casanova, David de la Croix, Aureo de Paula, Pascaline Dupas, Joe Hotz, Joe Price, George-Levi Gayle, Limor Golan, Gautam Gowrisankaran, Drew Griffen, Jim Heckman, Bart Hamilton, Josh Kinsler, Ashley Langer, Brian McManus, Bob Miller, Alex Monge-Naranjo, Alvin Murphy, Ronni Pavan, Bob Pollak, Mark Rosenzweig, Bernard Salanie, Seth Sanders, Jeff Smith, Chris Taber, Michele Tertilt, Christopher Walters, Ken Wolpin, Junjian Yi, Junsen Zhang, and participants at various seminars and conferences. All errors remain our own.

 https://doi.org/10.3982/QE2088

subtle phenomenon occurs, for example, when a mother of one, would like to enjoy the utility from this very same sex variety, but decides not to go for a second child because it might end up being of the same sex as the first one.[1] Here again, sex uncertainty produces an inefficient fertility outcome relative to a benchmark of perfect information. In recent years, however, highly accurate methods of sex selection have been developed that could in the near future be used to remove this uncertainty. Their use is of course subject to heated debate from a bioethical standpoint. However, if one puts aside, for the moment, issues of gender bias and resulting implications for the sex ratio, a standard economic perspective would consider sex selection as a welfare-improving technology that eliminates this "sex uncertainty" friction and allows parents to more precisely target the desired sex mix for their offspring.

In this paper, we do not weigh in on the debate on the bioethics of sex-selection technology but rather ask a simple positive question: what would be the demographic consequences of widely available, easily affordable sex-selection technology in a setting where some parents seek sex variety in their offspring? This is a simple question, but one that is quite difficult to answer in an empirically convincing way. Previous work has tackled the question mostly at the theoretical level or using simulations under assumed rules of fertility behavior. Work in demography, assuming somewhat rigid target fertility rules, has predicted substantial fertility declines in simulations of the consequences of sex predetermination.[2] Ben-Porath and Welch (1972, 1976) and Samuelson (1985) were among the first to bring the issue to the attention of economists. Ben-Porath and Welch (1976) were after the same question "how would the removal of uncertainty concerning the sex of children affect family size" and provided a clever back of the envelope calculation to gauge the potential impact of sex-selection technology. They found that fertility would decline, but much less than what was predicted by a demographic approach. The main problem for a credible answer to this question comes from the lack of any variation (let alone exogenous one) across time and/or space in meaningful exposure to sex-selection technology. As a result, a standard empirical strategy leveraging the fertility differences among those who are exposed (to sex-selection technology) and those who are not, is not available in the United States context.[3] To tackle the question, we then develop a simple dynamic model of sequential fertility decisions that features explicit preferences for sex variety. We leverage the *lack of* exposure to sex-selection technology and the quasi-experimental variation inherent in the plausibly random determination of sex at the time of fertilization to identify the key structural parameter characterizing preferences for sex variety. We estimate the model using data on couples from the National Survey of Family Growth who had no access to highly accurate, easily affordable,

[1] This notion was, to our knowledge, first discussed in demography by McLelland (1979).

[2] See, for example, McDonald (1973), Markle and Nam (1971), and Sheps (1963). The exercise goes as follows. The demographer posits that couples have an ultimate goal of, say, having at least b boys and g girls. She then proceeds to calculate the expected number of births that it takes to reach that goal. Not surprisingly, introducing sex-selection technology in this setup leads to large declines in completed fertility.

[3] Chen, Li, and Meng (2013) consider the roll-out of sex-selection technology in China during the 1980s and find that sex selection increased but do not look at completed fertility effects given the influence of the one-child policy.

sex-selection methods. Once the underlying preference structure is identified, we use the estimated model to conduct a simple counterfactual involving the introduction of a low-cost and widely acceptable sex-selection technology. Our results are somewhat surprising: in contrast to most findings in demography, which predict a large fertility reduction, we find this type of technology could lead to a much milder reduction of less than 2% in the average family size of married couples, which only declines from 2.28 to 2.24.[4] While we find that the key driver of fertility decisions is the desire for a diverse sex mix among offspring, we also find a slight preference for girls. This makes it more likely that firstborns are girls, even when boys are harder to obtain using sex selection and should be sought after first for strictly technological reasons. Indeed when the technology is not fully accurate, and accuracy depends on the sex of the child being sought, a large imbalance in the sex ratio can occur across the birth order as couples who seek a diverse sex composition in their offspring would attempt to first have a child of the sex that is more difficult to obtain.[5] Since first-born children have better life-cycle outcomes, our findings have intriguing implications for the evolution of gender gaps in those outcomes if this technology were to become widely used.

In sum, our structural approach recovers heterogeneous preferences for (a) the number of children, (b) a diverse sex mix, and (c) girls versus boys. This knowledge allows us to endogenously recompute fertility rules used by couples in counterfactual scenarios such as the one with sex-selection technology. Our approach may improve upon the traditional demographic approach, which directly posits an assumed fertility goal and simulates the resulting fertility that ensues as couples attempt to reach that goal with and without sex-selection technology. The rest of the paper is organized as follows. The next section presents a brief policy and technology background to provide some context for our analysis. Section 3 describes the data and presents some reduced form evidence suggestive of strong preferences for sex variety in the U.S. context. Section 4 presents the model while Section 5 describes the estimation strategy and provides some measures of model fit. Section 6 conducts counterfactual predictions assessing the demographic consequences of sex-selection technology. Conclusions follow.

2. Technology and policy background

Sex-selection technology

It is worth first getting some background on the technology of sex selection. Methods to select sex can be broadly distinguished by whether they select before or after fertilization. The latter usually raises more objections from a bioethical standpoint. We discuss sex selection before fertilization first. Various methods have been proposed to affect the chance of conceiving a child of a particular sex.[6] But the most effective, proven methods of sex selection before fertilization involve sperm separation techniques followed

[4]Previous work in economics has also suggested alternative ways in which the introduction of sex-selection technology could lead to an increase in fertility; see Leung (1994) and Davies and Zhang (1997).

[5]In particular, if there were no differential preferences for boys versus girls and accuracy is higher when seeking a girl, most firstborns would instead be boys.

[6]These methods vary in their scientific basis and most of them are not thought to be very reliable. They range from recommendations on the timing of intercourse during the woman's menstrual cycle (Rorvik and

by artificial intrauterine insemination (IUI) or *in vitro* fertilization (IVF) using a concentrated sperm subsample that contains mostly X- or Y-bearing chromosomes. As discussed in Hamilton, Jungheim, McManus, and Pantano (2018) among others, IVF can involve substantial out-of-pocket costs, particularly for those without insurance coverage. However, the vast majority of families pursuing sex selection do not have infertility problems requiring IVF. Thus, a simple IUI with the appropriate sperm subsample will suffice. Unlike IVF, artificial IUI is quite inexpensive.

The first sperm separation technique was pioneered by Ronald Ericsson in the 1970s and involves centrifugation (i.e., spinning) of a sperm sample. As the semen sample is spun, the heavier spermatozoa (carrying an X chromosome) segregate themselves away from the lighter, Y-bearing sperm. The Ericsson method provides a substantial improvement over a 50–50 coin flip but it is far from perfect.[7] More recently, a new sperm separation technique has been developed. It is called MicroSort and uses a different technology: since X chromosomes have more DNA than Y chromosomes, it is possible to identify them under laser light using a fluorescent material that attaches itself onto the DNA. Once the sperm carrying X and Y chromosomes has been labeled, a sorting procedure separates the X-bearing from the Y-bearing chromosomes, one by one. Early estimates indicated that MicroSort's technology would offer couples an 85% chance of conceiving a girl and a 65% chance of conceiving a boy; see Golden (1998). More recent estimates claim a success rate of up to 90% when seeking a girl and 75% when seeking a boy. The woman can then be artificially inseminated with the concentrated subsample of sperm carrying the desired chromosome. While these sperm separation techniques are not perfect, it is worth considering the possibility that they could be further perfected in the near future.[8]

It is also possible to sex-select after fertilization. In this case, one simply finds out the sex of the child that has already been conceived using some form of prenatal sex diagnoses, such as chorionic villus sampling, amniocentesis, or ultrasound.[9] A sex-selective abortion is then conducted whenever the developing pregnancy is of an unwanted sex.[10]

Shettles (1970), Whelan (1977), James (1983)) to a woman's diet (Lorrain and Gagnon (1975), Stolkowski and Choukroun (1981), Warren (1985), Langendoen and Proctor (1982) or the provision of acidic (for boys)/alkaline (for girls) environments for sperm (Rorvik and Shettles (1970)). An alternative, more invasive approach involves injecting the woman with antibodies against Y- or X-bearing sperm (Bayles (1984) and Hull (1990)). None of these methods have been proven to be reliable.

[7] Beernink, Paul Dmowski, and Ericsson (1993) report a success rate of approximately 70%, with more recent variants of this method providing improved rates.

[8] At the time of this writing, the developers of MicroSort have not yet sought FDA approval for mass-market deployment of this technology within the U.S.

[9] More recently a noninvasive prenatal testing (NIPT) technique based on cell-free fetal DNA (cfDNA) has been developed that can provide information about a fetus's sex as early as 9 weeks of gestation. Insurers are beginning to cover this test, which provides an alternative to traditional genetic screening based on amniocentesis or chorionic villus sampling.

[10] Most research on sex-selection technology has focused on the case of gender bias in contexts with more widespread use of sex-selective abortion. See, for example, Leung (1994) for a hazard-based estimation of the effects of son-preference and sex selection on fertility among chinese women in Malaysia. See also Leung (2011) for quantitative work on sex-selective abortions in the context of China's one-child policy and Anukriti (2018) for the analysis of the tradeoff between sex preferences and family size in the context of a fertility control intervention in India.

This method raises additional issues from a bioethical standpoint, especially when compared to methods that sex-select before conception. It is also difficult to implement, as ultrasounds for sex determination are usually performed late in pregnancy and at that time it is usually too late to find a provider willing to conduct an abortion. Moreover, while attitudes toward abortion are fairly divided in the U.S., a clear majority opposes abortion when the only reason is undesired sex. Given implementation difficulties and strong public opinion opposition, sex-selective abortions remain quite rare in the United States, relative to other countries like India or China.[11] Amniocentesis and chorionic villus involve risks to the fetus and are generally indicated only for women at high risk of developing pregnancies with genetic abnormalities.

Finally, an alternative method of sex selection after conception (but before implantation) is in-vitro fertilization (IVF) followed by prenatal genetic diagnosis (PGD). PGD's primary role is to screen embryos for genetic abnormalities. But it can also be used to determine their sex. Then one can simply transfer only embryos of desired sex back into the uterus. While IVF+PGD is quite accurate, mechanical sperm separation followed by artificial insemination is arguably much less invasive and substantially less expensive. As a result, it has a much larger potential demand by typical couples without infertility problems.

Regulatory and policy background

The use of sex-selection technology for non-medical reasons before conception is explicitly banned in several developed countries and no country explicitly *allows* sex selection for nonmedical reasons.[12] But in many developing countries, the legal status of this practice is not clear or well-defined. Similarly, in the U.S. there is no official ban on the use of these methods, but relevant medical organizations such as the American Medical Association (AMA) and the American Society for Reproductive Medicine (ASRM) periodically discourage them through their ethical guidelines.

Given the lack of an explicit ban and despite discouragement from appropriate organizations, sex-selected babies for nonmedical reasons are currently being born in the U.S. through both Ericsson's method and IVF+PGD. However, the practice is not widespread due to issues of accuracy, invasiveness, and cost. As explained above, while Ericsson's method is somewhat affordable and not very invasive, it is not that accurate. On the other hand, while IVF+PGD is highly accurate, it is quite invasive and extremely costly. It is likely that under the current, relatively lax, regulatory framework, a perfected technology that simultaneously provides an affordable, minimally invasive, and highly accurate sex-selection experience before conception will have the potential for almost universal demand. The only remaining barrier for widespread adoption would at that point be only an ethical or religious one. But again, "before conception" methods tend to

[11] As described in Rebouche (2015), some states (Illinois, Pennsylvania, Oklahoma, Arizona, North Carolina, Kansas, North Dakota, and South Dakota) have already established bans on sex-selective abortion. In addition, a potential federal law has been debated in the U.S. Congress.

[12] Israel has recently allowed it for families with extremely unbalanced sex ratios (couples with 4 or more children of one sex and none of the other); see Siegel-Itzkovich (2005).

raise fewer issues on these dimensions, too. For example, some of the arguments made in support of bans against sex-selective abortions do not apply in this case. It is not far-fetched then to entertain a scenario in which such perfected technology generates a sex-selection demand boom and forces a more widespread discussion across society on the appropriate framework needed to regulate this type of procedure. Until then, the environment is likely to continue to be one of suggested discouragement instead of explicit prohibition. For example, on the issue of sex selection before conception, the Council on Ethical and Judicial Affairs of the American Medical Association has stated that "sex selection of sperm for the purposes of avoiding a sex-linked inheritable disease is appropriate." At the same time, the Council suggested that "physicians should not participate in sex selection for reasons of sex preference" but "should encourage a prospective parent or parents to consider the value of both sexes."[13] Similarly, the Ethics Committee of the American Society of Reproductive Medicine states that "preimplantation genetic diagnosis used for sex selection to prevent the transmission of serious genetic disease is ethically acceptable," but goes on to recommend avoidance of the procedure when solely used for sex selection by stating that "…The initiation of IVF with PGD solely for sex selection … should be discouraged."[14]

3. Data and source of exogenous variation

To estimate our model, we use data from the National Survey of Family Growth (NSFG). The NSFG, conducted by the National Center for Health Statistics, gathers retrospective information on the fertility histories of a random sample of women 15–44 years of age in the civilian, noninstitutionalized population of the United States. In particular, for each woman, we have the year of birth and sex of each of her children.

We use the birth histories of married female respondents by the time of interview to recover the fertility choices each of these women made in each period (starting at age at marriage and leading up to the age at the time of the NSFG interview). The age at the time of interview varies from 15 to 44 and, therefore, we have fairly complete histories for some of the oldest women in the sample, and very short, censored histories for the youngest ones. In constructing this unbalanced panel, we assume that if a live birth is observed for female i at age $a+1$, then she became pregnant with that child at age a.[15] The NSFG also allows us to see if and when a woman chose to undergo sterilization at any point in her life before the interview. In addition to fertility histories, the NSFG also provides information on the completed years of education that these women have achieved by the time of interview. We use completed years of education by an interview to classify NSFG women into low education and high education groups. The high education group includes women with at least some college. The low education group

[13] See the American Medical Association (1993).

[14] See Ethics Committee of the American Society for Reproductive Medicine (2004). ASRM also discourages sex selection when sex determination through PGD is obtained as a by-product of PGD initiated for legitimate medical reasons.

[15] For simplicity, we organize the panel at the annual level, the unit of time to be used in the model below, as opposed to 9-month intervals, which is of course more accurate.

includes those who graduated from high school and high school dropouts. Since some women are too young at the time of interview to have completed their education, we restrict our sample to those who were 25 years of age or older at the time of the interview. Finally, we use the information on the reported pregnancy intention associated with each of the woman's births. We can distinguish between births that were intended and those that were unintended. Distinguishing between intended births and unintended ones provides a key advantage of NSFG over other potential data sources like the population census. It is important to allow for unintended births in our model because the technology we evaluate in our counterfactual experiment can only be applied to intended pregnancies. Two of the choices in the model we describe below in Section 4 are (1) to willfully pursue a pregnancy during age a, (in which case an intended pregnancy occurs with probability one during that year and a birth occurs at age $a+1$) and (2) engage in temporary contraception at age a (in which case either no pregnancy occurs or an unintended pregnancy occurs with probability less than one during that year and an unintended birth occurs age $a+1$). We use the data on pregnancy to capture these model choices in the microdata. In particular, the first choice in the model "pursue pregnancy" ($j=1$) is defined retroactively at age a upon the observation of a birth at $a+1$ that is reported by the mother to be the result of an intended pregnancy, conceived at age a. Similarly, the option "temporary contracept" ($j=2$) is defined retroactively at age a upon the observation of either no birth at $a+1$ (in which case the "temporary contraception" measures must have succeeded) or the birth of a child at $a+1$ that is reported to be the result of an unintended pregnancy conceived at age a (in which case the "temporary contraception" measures failed).

Our final estimation sample consists of 8137 female respondents aged between 25 and 44 at the time of interview, using several NSFG waves spanning 1982–2008.[16] We focus on the subsample of married women who have been involved in a single marriage and who remain married by the time of the interview. By focusing on married women, we abstract away from issues associated with the joint modeling of marriage and fertility. We drop women who had a first live birth before the age of 16, those who have ever had multiple live births in a single year, and those who had their first birth before marriage. We also exclude women who report ever having infertility problems.

Table 1 presents the distribution of completed fertility by the time of interview. Column 1 shows numbers for the entire sample whereas columns 2, 3, and 4 are restricted to those who are at least 40 years old at the time of interview. These women are very unlikely to have additional births after the interview and, therefore, provide a better way of gauging the eventual patterns of completed fertility among NSFG women. Column 2 looks at all education levels, whereas columns 3 and 4 focus on subsamples of low and high education groups. Of course, the patterns of completed fertility among 40+ women are quite different from that in the entire sample. Mechanically, these women have had more time to have children and so the distribution shifts away from childlessness and low parities. Also, as well documented elsewhere, women with more education

[16]The NSFG cycles included in our sample are NSFG 1982, NSFG 1988, NSFG 1995, NSFG 2002, and the first part of the NSFG 2006–2010 continuous wave, released in May 2010.

TABLE 1. Completed fertility by time of interview.

	All Women	Women 40+ All Edu	Women 40+ Low Edu	Women 40+ High Edu
0	17.9%	8.3%	6.6%	9.4%
1	20.3%	11.0%	10.9%	11.1%
2	38.8%	46.2%	42.2%	48.6%
3	16.6%	23.4%	24.9%	22.4%
4	4.7%	7.6%	9.5%	6.5%
≥5	1.7%	3.6%	5.9%	2.1%
Obs.	8137	1627	623	1004

Note: Sample restricted to married women who were 25 and older at time of interview. Pooled samples from NSFG waves 1982–2008.

tend to have fewer children. Another important difference between high and low education women is related to the timing of births. Figure 1 shows that the distribution of age at first birth peaks at a much later age for highly educated women. The modal age at first birth is 21 for those with low education and 26 for those with high education. Table 2 shows the distribution of sex-specific completed fertility at the time of interview. As can be seen in the table, completed fertility follows a fairly symmetric pattern, an indication that sex bias is less apparent in the U.S. than in countries like India and China. Figure 2 provides the main choice patterns in the data. Married women pursue pregnancies at high rates early in their reproductive careers and then tend to contracept at older ages. The share of ever sterilized women grows steadily across age. By age 44, more than 35% of women are sterilized. Women with higher education tend to pursue pregnancies later and tend to sterilize at a lower rate. Conditional on temporarily contracepting, the probability of an unwanted birth is very high in the late teenage years and steadily declines at older ages. Highly educated women have a much lower probability to have unwanted

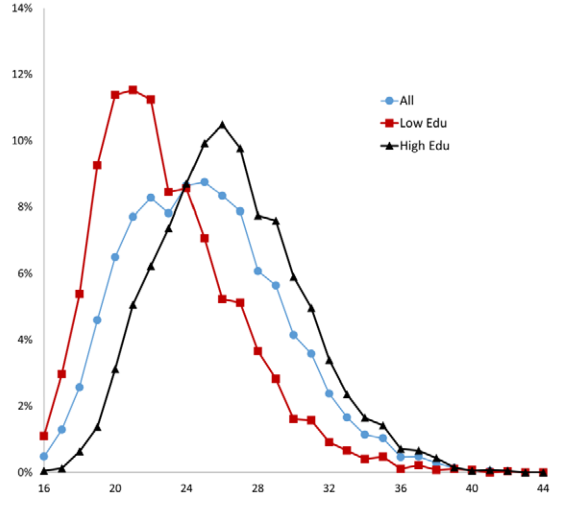


FIGURE 1. Distribution of age at first birth by education.

TABLE 2. Sex-specific completed fertility by the time of interview.

		Number of girls					
		0	1	2	3	4	Total
Number of boys	0	8%	6%	10%	2%	1%	27%
	1	5%	23%	9%	1%		38%
	2	13%	8%	3%			24%
	3	4%	2%				6%
	4	1%					1%
	Total	31%	39%	22%	4%	1%	96%

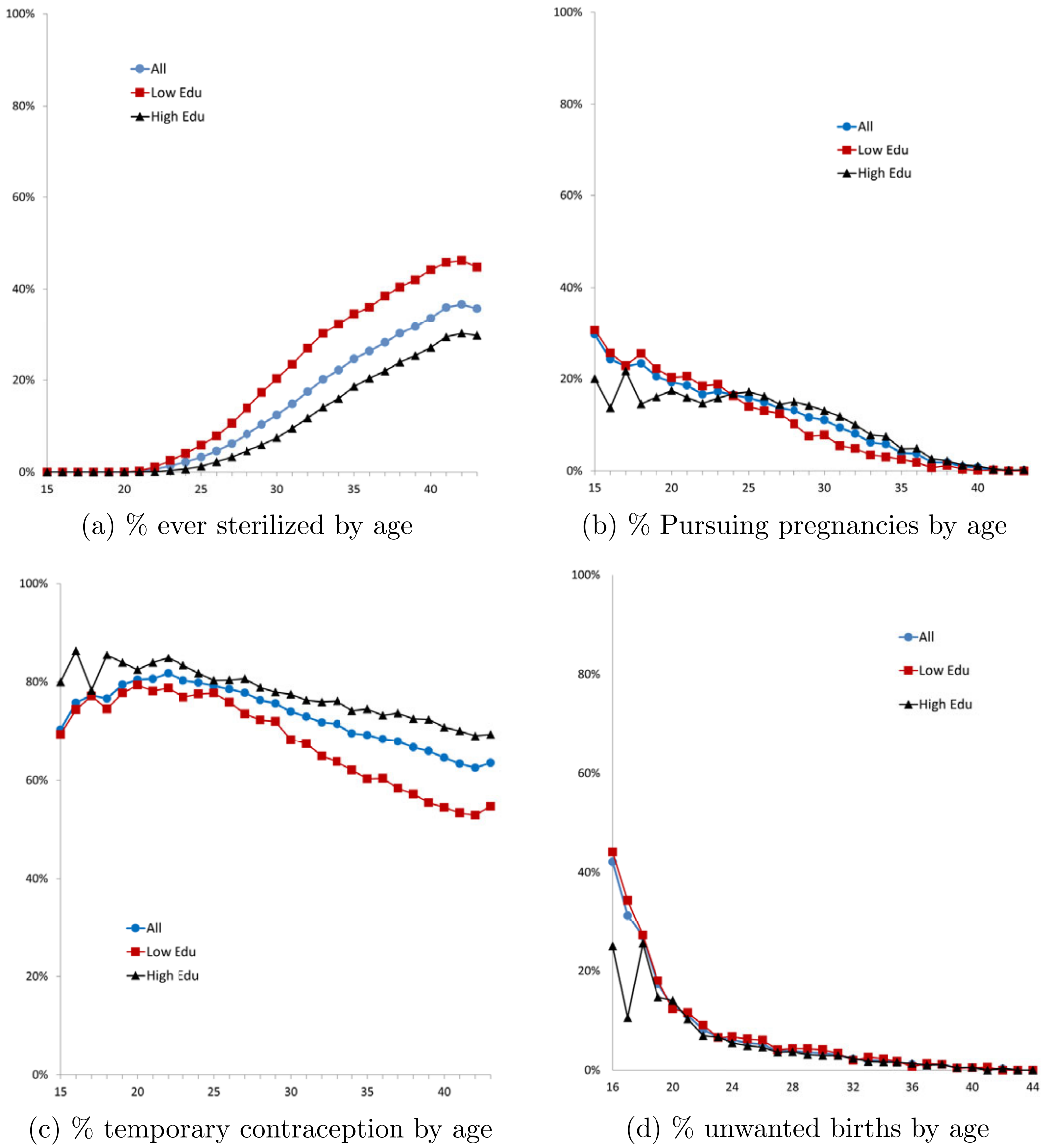
Note: Sample restricted to women 40 and older at time of interview. Pooled samples from NSFG waves 1982–2008. Table shows only 96% of women with 4 or less children at time of interview.

births. While there is no overt evidence of sex-biased preferences in the United States, Ben-Porath and Welch (1976) and Angrist and Evans (1998) present suggesting evidence of strong preferences for sex variety by noting that parents who have not reached sex variety (at least one boy and one girl) in their offspring are much more likely to continue their fertility.[17] Table 3 presents similar evidence that we obtain from the NSFG data, which allows us to further examine these propensities to have additional children separately depending on their associated pregnancy intention status as retrospectively reported by their mothers.

Consider women at parity $n = 2$. As can be seen in panel A for the probability of eventually having another *wanted* child, those who had two girls and no boys or two boys and no girls have a much higher probability of going on to have another child (25% and 28%) than those who already have one boy and one girl (21%). This clear difference in the propensity to willfully continue fertility is not present in panel B, which examines the probability of eventually having another child who turns out to be *unwanted* in the sense that it was conceived at a time in which the mother was planning to have no further children. For $n = 2$, this probability is around 13–14% regardless of sex composition. While sample sizes are smaller at higher parities, one can still detect the same pattern of higher propensity to continue fertility at $n = 3$ and $n = 4$ for those who still have no boys or no girls among their offspring.

While these patterns are interesting and useful in their own right, they do not allow us to predict the demographic consequences of sex-selection technology. Whenever a woman with two children of the same sex decides not to go for another child, we cannot tell whether she would have gone for it, had the technology to secure its sex been available. In other words, for women who ideally would have liked to have one boy and one girl, but ended up having two children of the same sex, we cannot distinguish whether the decision not to go for a third child stems primarily from a lack of strong preferences for variety or from the potential reduction in utility associated with having three children of the same sex, if the third child turns out to have the same sex as the first two.

[17] Rosenzweig and Wolpin (2000) lay out specific assumptions on preferences and household technology under which this type of empirical evidence can be interpreted as preferences for sex variety.



(a) % ever sterilized by age

(b) % Pursuing pregnancies by age

(c) % temporary contraception by age

(d) % unwanted births by age

FIGURE 2. Data patterns by age and education.

To move forward, in the next section we write an estimable model that can potentially generate these patterns discussed above and that adds the least possible structure needed to answer our research question: what would be the demographic consequences of widely available, easily affordable, sex-selection technology?

4. A DYNAMIC MODEL OF SEQUENTIAL FERTILITY DECISIONS

Beginning with Wolpin (1984), there is a growing literature on structurally estimable microeconomic models of fertility in which reproductive behavior is the result of a sequen-

TABLE 3. Probability of having another child by sex mix of existing children and pregnancy intention status of additional child.

		Number of girls				
		0	1	2	3	4
				A. Pr(Wanted Child)		
Number of boys	0	67%	59%	25%	22%	21%
	1	63%	21%	17%	18%	
	2	28%	15%	12%		
	3	18%	13%			
	4	25%				
				B. Pr(Unwanted Child)		
Number of boys	0	15%	15%	14%	14%	9%
	1	14%	13%	11%	9%	
	2	13%	11%	12%		
	3	8%	14%			
	4	10%				

Note: Pooled samples from NSFG waves 1982–2008. Panel A refers to the probability that women go on to have another child described as wanted between the last birth (associated with the given sex-specific combination given in the row and column) and the time of interview. A given woman may contribute to multiple cells in the table. Panel B presents a similar probability for going on to have an unwanted child. Probabilities in each cell of Panels A and B are unconditional. If one also adds the probability of not having another child, the three probabilities would add up to 100%.

tial, dynamic process, associated with the optimal decision-making of forward-looking agents. Arroyo and Zhang (1997), Hotz, Klerman, and Willis (1997), and Wolpin (1997) summarize this line of work.[18] However, these models have not been generally used to estimate preferences for sex variety and to predict the consequences of sex-selection technology.[19]

In this section, we write a formal estimable model that allows for preferences for sex variety. In particular, we incorporate explicitly a specification of preferences for a diverse sex mix in the spirit of Rosenzweig and Wolpin (2000).[20] This is the crucial added feature of our model.[21]

[18]Early papers by Becker (1960), Willis (1973), and Becker and Lewis (1973) pioneered the study of completed fertility in a static, single-shot context in which the entire life cycle constitutes a single decision period. Building on this early work, Ben-Porath and Welch (1972) and Heckman and Willis (1976) were among the first to think about issues of sequentiality, dynamics, and uncertainty.

[19]Ebenstein (2011) estimates a model of sex selection for China using a different framework that allows for sex selection as part of the data generating process, but abstracts from issues of fertility timing and spacing.

[20]We do not distinguish whether a specific sex-composition effect enters directly through children services in the flow utility or through its potential impact on household consumption opportunities through the budget constraint. Rosenzweig and Wolpin (2000) highlight the fact that lack of sex variety may generate "hand me down" cost savings, as children of the same sex can use the same clothes or share a bedroom for a much longer time. While this distinction is clearly important in other contexts, it is not necessary to separately identify these two channels to answer our research question.

[21]Ahn (1995) was the first to allow the value of children to vary by sex in an estimated dynamic programming model of fertility. However, while allowing for sex differences in the value of children, his model does not allow for explicit parental preferences for sex variety. More recent structural work in fertility has begun to allow preferences for children to directly vary with sex mix; see Lavado (2014), among others.

Our model is deliberately simple. We abstract away from a rich modeling of life-cycle variation in income and the cost of children, perhaps more critical for other research questions. We do not model other important decisions that are arguably made jointly with fertility and could therefore be affected in our counterfactuals: schooling, labor supply, marriage, and investment in children. Perhaps an explicit joint modeling of female fertility and labor supply would be of more primary concern if our goal here was, say, to analyze maternity leave or child care subsidy policies. Yet, our focus here is completely different. We will focus on exploring the demographic consequences of a sex-selection technology that could allow parents to satisfy their specific preferences for a balanced sex composition. As a result, in what follows we abstract away from a detailed economic modeling of the determinants of timing and spacing of births and sidestep specific issues related to the joint modeling of female fertility and labor supply and other demographic behavior.[22] We do not explicitly model abortion decisions.[23] While abstracting from an explicit economic modeling of timing and spacing, we retain the sequential, dynamic framework to properly handle sex uncertainty. Parents in our model have reproductive policy functions that can potentially depend on (are contingent upon) the realized sex of each child. In other words, some parents may need to wait and see what the sex mix of their first two children is, before deciding on whether to seek a third pregnancy. This requires a dynamic model.

We develop a simplified version of the model in Carro and Mira (2006), augmented to allow for preferences for a diverse sex mix. First, we let $d_a = 1$ denote the decision to pursue pregnancy at age a that results in a live birth with certainty next period at age $a+1$. Second, we let $d_a = 2$ indicate the choice of temporary, imperfect contraception, which makes pregnancy and a live birth next period a probabilistic event. Third, we denote by $d_a = 3$ the decision to engage in permanent, perfect contraception through sterilization. Note that sterilization represents a terminal action in the model, which if chosen, prevents the woman from making subsequent fertility decisions.

Let the state vector at age a be $x_a = [a, n_a^b, n_a^g, e, \underline{A}]$ where a is age in years, n_a^b is the number of boys by age a, n_a^g is the number of girls by age a, e is an indicator for low $(e = 0)$ or high $(e = 1)$ education, and $\underline{A}$ denotes age at marriage. There is also an implicit auxiliary state variable that keeps track of whether the woman is still fertile and, therefore, can freely make any of the three choices. It is equal to one at marriage and switches to zero when the woman either sterilizes or reaches age $\overline{A}$.

Period utility for choice d is given by

$$u_{da}(x_a) + \varepsilon_{da}, \tag{1}$$

where ε_{da} is an i.i.d. (across individuals, ages, and alternatives) preference shock to the utility of alternative d. We assume that ε_{da} has Type 1 Extreme Value distribution with

[22] For work on the joint modeling of female fertility and labor supply, see Moffitt (1984), Hotz and Miller (1988), Francesconi (2002), Gayle and Miller (2012), and Adda, Dustmann, and Stevens (2017). See also Keane and Wolpin (2010) who focus on a woman's welfare participation decision, but model her fertility and labor supply as joint related choices.

[23] For recent detailed and explicit modeling of abortion decisions in dynamic structural models of fertility, see Forsstrom (2016) and Amador (2017).

a zero mean. To simplify the exposition, the systematic component $u_{da}(x_a)$ can be factored into two terms

$$u_{da}(x_a) = \overline{u}(x_a) + \mu_d(e), \tag{2}$$

where $\overline{u}(x_a)$ is independent of d and captures net flow utility from children and depends on number and sex composition in the current stock of children as follows:

$$\begin{aligned}\overline{u}(x_a) = {} & \eta_1 I_{1a} + \eta_2 n_a + \eta_3 n_a^2 \\ & + \eta_4 I\{n_a^g \geq 1 \cap n_a^b \geq 1\} + \eta_5 I\{n_a^b \geq 1\} \\ & + \gamma_1 I\{e=1\} I_{1a} + \gamma_2 I\{e=1\} I_{2a} + \gamma_3 I\{e=1\} I_{3a},\end{aligned} \tag{3}$$

where $I_{ma} = I\{n_a \geq m\}$.[24] This specification includes a term (η_1) that captures the utility from having at least one child. It also includes a quadratic in n_a, which captures the flow services in the utility function from the stock of children that a woman has had by any age, regardless of sex (i.e., $n_a = n_a^b + n_a^g$). The quadratic allows the marginal utility from additional children to eventually become negative and rationalize the fact that most women have 4 or less children despite having a reproductive potential of 29. This is coupled with an indicator $I\{n_a^g \geq 1 \cap n_a^b \geq 1\}$ representing the extra utility obtained when having achieved sex variety in offspring by age a. Our definition of sex variety is the simplest possible: as long as a woman has at least one child of each sex (i.e., $I\{n_a^g \geq 1 \cap n_a^b \geq 1\}$), we shift her utility by η_4.[25] We also allow education to nonparametrically affect the utility from children through the indicators I_{ma} for $m \in \{1, 2, 3\}$ and the associated parameters γ_m.[26] The key parameter in our context is η_4, which captures the extent of preferences for sex variety.[27] Finally, while the descriptive results in Section 2 indicate that preferences for boys versus girls might not be particularly important for the U.S. (at least in comparison with other countries where a marked preference for boys is present), we do allow for such preferences in the model. Even slight preferences for either boys or girls could have large effects in our counterfactuals, given that we consider the introduction of a technology that would be essentially costless.

[24]The static flow utility from choices does not depend on the term $\overline{u}(x_a)$. But the individuals are forward-looking and, therefore, choice j at age a affects $\overline{u}(x_{a+1})$.

[25]One could also model preferences for sex variety in a more complex way by increasingly penalizing utility as the offspring's sex ratio deviates from 1 as in Rosenzweig and Wolpin (2000). We feel the underlying reason for having preferences for variety is that some parents may wish to experience both things that are more typically associated with the raising of a girl and things that are more typically associated with raising a boy. These basic utility-yielding experiences for the parents can be equally satisfied as long as they have at least one child of each sex. Furthermore, the data does not show as much of a contrast in the pursuit of wanted pregnancies after (3, 1) or (1, 3) versus (2,2) as the one we observe after (2, 0) or (0, 2) relative to (1, 1) providing further justification for our modeling choice.

[26]An alternative would be to introduce education differences in the utility from offspring by letting the linear and quadratic terms vary by education group. This would be more symmetrical but less flexible to model the parental education differentials in fertility in the critical range (at parities 1, 2, and 3).

[27]While we attach a strict preference interpretation to η_4, this parameter may capture the combined effect of direct preferences for variety and the utility gains associated with potential cost savings. The cost-saving interpretation is more plausible in a developing country context. Preferences for sex-balanced offspring are seen as more relevant for the U.S.

Since $\mu_1(e)$ is normalized to zero, the term $\mu_d(e)$ captures, in a reduced form fashion, the net costs or benefits associated with choice $d = 2, 3$ (temporary and permanent contraception) relative to the choice of deliberately pursuing pregnancy $(d = 1)$. We specify $\mu_2(e) = \mu_2$ for all e and $\mu_3(e) = \mu_3 + \mu_3^h e$.

Once a woman chooses sterilization at age a, she no longer makes choices from age $a + 1$ onward, but continues to receive the flow utility associated with the stock of children she had at the time of sterilization. Therefore, the value of choosing sterilization $(d = 3)$ at age a with state x_a, net of ε_{3a} is given by

$$v_{3a}(x_a) = u_{3a}(x_a) + \sum_{\tau=a+1}^{\widetilde{A}} \beta^{\tau-a} \overline{u}(n_a^g, n_a^b, e), \tag{4}$$

where $\widetilde{A}$ is the last period of life.[28]

At each and every year after marriage, women choose to pursue pregnancy to give birth to a child next period, engage in temporary contraception, or pursue a permanent form of contraception by choosing to sterilize.[29,30] The transition probability for the state variables that keep track of the sex-specific stock of children is denoted by $f_{da}(x_{a+1}|x_a)$.[31] Given the random determination of sex at conception, we have[32]

$$\Pr\bigl(n_{a+1}^b = n_a^b + 1 \cap n_{a+1}^g = n_a^g | d_a = 1\bigr) = 0.512, \tag{5}$$

$$\Pr\bigl(n_{a+1}^b = n_a^b \cap n_{a+1}^g = n_a^g + 1 | d_a = 1\bigr) = 0.488. \tag{6}$$

Also, since the model allows for unwanted pregnancies, to complete the characterization of $f_{da}(x_{a+1}|x_a)$ we need to specify the transition probability for an unintended birth the next period, given the choice of temporary and imperfect contraception in the current period, which is another primitive of the model.[33] In other words, we need to specify

[28]We abstract away from infant mortality. This is perhaps a more relevant issue in models of fertility in less developed countries; see Wolpin (1984) and Mira (2007). In our model, all children survive.

[29]Wolpin (1984), Ahn (1995), and Gayle and Miller (2012) assume that fertility can be perfectly controlled. We follow Rosenzweig and Schultz (1985), Montgomery (1988), Hotz and Miller (1988, 1993), and Carro and Mira (2006) by considering a dynamic model of fertility with stochastic reproduction and contraception. See also David and Mroz (1989) who describe how conception hazards evolve with successive demographic events. While we allow for imperfect contraception, we abstract away from infertility issues due to data limitations. See Carro and Mira (2006) for a model with unobserved heterogeneity in fecundity. We also assume that women are sexually active from age 15 onward. See Arcidiacono, Khwaja, and Ouyang (2012) for a model of sexual activity onset.

[30]Technically, since we model neither frequency of sexual activity nor decisions to terminate unintended pregnancies, the choice of temporary contraception $d = 2$ actually includes abstinence and abortion as extreme forms of "temporary contraception."

[31]We abstract away from the possibility that parents may revise these transition probabilities over time. For example, after having 3 boys and no girls, a couple continues to hold the belief that the probability of having a girl in the next attempt is still approximately 50%. See Ben-Porath and Welch (1972, 1976).

[32]Technically, the probabilities of having a boy or a girl are 51.2% and 48.8%, respectively. We use these probabilities to capture beliefs when solving the dynamic program and for actual transitions when simulating it.

[33]We feel it is important to distinguish between wanted and unwanted pregnancies in estimating preferences for the number of children. Ignoring pregnancy intention and abstracting from contraceptive choice

an aggregate probability of contraceptive failure.[34] We assume that it depends on age a, education e,

$$\Pr(n_{a+1}=n_a+1|d_a=2,a,e)=\Lambda\big(\zeta(a,e)\big), \tag{7}$$

where $\Lambda()$ is the logistic distribution and

$$\zeta(x_a)=\lambda_0+\lambda_1\left(\frac{a-14}{30}\right)+\lambda_2\left(\frac{a-14}{30}\right)^2+\lambda_3\left(\frac{a-14}{30}\right)^3+\lambda_4 e. \tag{8}$$

Children born out of unintended pregnancies are also approximately equally likely to be boys or girls. Beginning at the time of marriage, married women maximize expected remaining lifetime utility by choosing the optimal quantity, timing, and spacing of births,

$$\max_{\{d_a\in\mathcal{D}(s_a)\}_{a=\underline{A}}^{\overline{A}}} E\left[\sum_{a=\underline{A}}^{\widetilde{A}}\beta^{a-\underline{A}}\left\{\bar{u}(x_a)+(1-s_a)\sum_{j=1}^{3}1\{d_a=j\}\big[\mu_j(e)+\varepsilon_{ja}\big]\right\}\right], \tag{9}$$

where $\underline{A}$ is the age at marriage, $\overline{A}$ is the last year in which the woman can pursue pregnancy, and β is the discount factor.[35] $\mathcal{D}(s_a)$ is the choice set at each age, which depends on an indicator s_a, which equals one if the woman has already sterilized before age a. $\mathcal{D}(1)=\emptyset$ and $\mathcal{D}(0)=\{1,2,3\}$. The economic trade-off in the dynamic optimization problem is straightforward. If children provide services in the flow utility, women may have an incentive to have them as soon as possible to enjoy them the most. However, for reasons not structurally modeled here, women must optimally wait for an age in which it is especially appropriate to have a birth (i.e., an age at which they receive a large ε_1).[36] Yet, they are fully aware that their reproductive years are limited and so their optimal policy functions take into account the approaching menopause age, assumed to occur at age $\overline{A}+1$, with probability one. A woman becomes less selective regarding the required ε_1 as she ages. Given the possibility of unintended births, women may engage in a precautionary fertility strategy as pointed out by Keyfitz (1971) and Heckman and Willis (1976), to avoid ending up with an excessive number of children in our multiperiod framework. Sterilization allows couples to eliminate risks of unintended births with certainty, but at the cost of forgoing the option value of additional fertility.

One can rerewrite the dynamic optimization problem into a standard recursive form by considering the choice-specific value functions (net of preference shock ε_{da}) v_{da} for

would lead to an overestimation of preferences for the number of children as the structural parameters capturing preferences for quantity would need to rationalize not only children that couples choose to have, but also those that are born but they would have preferred not to have.

[34]Due to data limitations, we do not model the particular choice of contraceptive method. Different contraceptive methods have different cost and failure rates.

[35]We use $\overline{A}=43$ and $\widetilde{A}=75$ and fix the discount factor at $\beta=0.95$.

[36]Two economic reasons to delay births are (a) the existence of borrowing constraints and (b) the fact that early births, especially in the late teens, can make it very difficult for a woman to achieve her optimal level of education. On the other hand, the opportunity costs of births increase with labor market experience and this is another factor that tends to induce earlier births; see Newman (1988) and Hotz, Klerman, and Willis (1997).

$d = 1, 2$ as follows:

$$v_{da} = u_{da}(x_a) + \beta \sum_{x_{a+1} \in X_{a+1}} E_\varepsilon \Big[\max_{j \in \mathcal{D}(0)} \{ v_{j,a+1}(x_{a+1}) + \varepsilon_{j,a+1} \} \Big] f_{da}(x_{a+1} | x_a). \tag{10}$$

The model has the potential to generate the type of findings in the work of Angrist and Evans (1998) and documented above for our sample. In particular, $\eta_4 > 0$ implies that women who, by age a have either $(n_a^b = 2, n_a^g = 0)$ or $(n_a^b = 0, n_a^g = 2)$ will have a larger probability of having another (a third) birth than those who have $(n_a^b = 1, n_a^g = 1)$.

5. Structural estimation

To estimate the model, we solve the dynamic programming problem through backward recursion for given structural parameters and embed this solution in an estimation routine that searches for the structural parameters that make the fertility histories predicted by the model as close as possible to those observed in the data, in a maximum likelihood sense.[37] We allow for unobserved heterogeneity by considering a discrete distribution of types in the population of married couples. We consider $K = 3$ types and we allow preference parameters $(\eta_{2,k}, \eta_{4,k}, \eta_{5,k})$ as well the intercept in the probability of having an unwanted birth $(\lambda_{0,k})$ to vary by type k.[38] However, to ensure representation of households that are indifferent about the sex of their offspring, we eliminate preferences for both sex variety and preferences boys versus girls among those couples of type 1 by setting $\eta_{4,1} = 0$ and $\eta_{5,1} = 0$. By enforcing exactly zero preferences we guarantee that these households will not use the technology, even when it is free as they should not derive any benefit from its usage.[39] We specify the probability that a couple is of type k as being a function of the woman's level of education e_i and her age at marriage $\underline{A}_i$,

$$\Pr(k | \underline{A}_i, e_i) = \frac{\exp(\xi_k(\underline{A}_i, e_i))}{\sum_l \exp(\xi_l(\underline{A}_i, e_i))} \tag{11}$$

with

$$\xi_k(\underline{A}, e) = \delta_{0,k} + \delta_{1,k}\left(\frac{\underline{A}_i - 14}{30}\right) + \delta_{2,k}\left(\frac{\underline{A}_i - 14}{30}\right)^2 + \delta_{3,k} e, \tag{12}$$

[37]While we estimate the model using standard maximum likelihood techniques, in principle, the model could also be estimated using the sequential EM algorithm proposed by Arcidiacono and Jones (2003) or the CCP methods proposed by Arcidiacono and Miller (2011) exploiting the terminal action property of our model.

[38]While we do not allow η_4 to vary directly with education, this will be captured in part by letting the type probability depend on education.

[39]Norling (2016) documents heterogeneity in preferences over the sex of children and argues that in many countries a substantial share of the population does not have such systematic preferences. Moreover, an unrestricted model without such normalizations would not be identified.

where we normalize the parameters for type 1 to zero ($\delta_{0,1}=\delta_{1,1}=\delta_{2,1}=\delta_{3,1}=0$). The parameters to be estimated are then

$$\theta=\begin{pmatrix}\theta_1\\ \theta_2\\ \theta_3\end{pmatrix}=\begin{pmatrix}\{\{\lambda_{0,k}\}_{k=1}^3,\lambda_1,\lambda_2,\lambda_3,\lambda_4\}\\ \{\eta_1,\{\eta_{2,k}\}_{k=2}^3,\eta_3,\{\eta_{4,k}\}_{k=2}^3,\{\eta_{5,k}\}_{k=2}^3,\gamma_1,\gamma_2,\gamma_3,\mu_2,\mu_3,\mu_3^h\}\\ \{\delta_{0,k},\delta_{1,k},\delta_{2,k},\delta_{3,k}\}_{k=2}^3\end{pmatrix}. \tag{13}$$

The key component of the likelihood function is the individual likelihood contribution,

$$L_i(\theta_1,\theta_2,\theta_3;x_i,d_i)=\sum_k \Pr(k|\underline{A}_i,e_i,\theta_3)L_i(\theta_1,\theta_2;x_i,d_i,k). \tag{14}$$

Let A_i^{nsfg} be the age at the time of the NSFG interview for woman i. The type-specific likelihood contribution for woman i, with given history of states and choices,

$$\left(\{d_{ia}\}_{a=\underline{A}}^{A_i^{nsfg}-1},\{x_{ia}\}_{a=\underline{A}}^{A_i^{nsfg}}\right),$$

is the probability of observing the sequence of fertility choices that she made and fertility transitions that she experienced as a result of those choices in the event that she is of unobserved type k. Since the shocks to preferences ε are i.i.d. over time, the type-specific likelihood contribution is given by

$$\begin{aligned}&L_i(\theta_1,\theta_2;x_i,d_i,k)\\&\quad=\prod_{a=\underline{A}_i}^{A_i^{nsfg}}\left[\prod_{j=1}^{3}\left\{\Pr(d=j|x_{ia},k,\theta_1,\theta_2)f_{ja}(x_{i,a+1}|x_{ia};k,\theta_1)\right\}^{I\{d_{ia}=j\}}\right],\end{aligned} \tag{15}$$

where $\Pr(d=j|x_{ia},k,\theta_1,\theta_2)$ is the model-predicted probability that an individual i who is at state x_{ia} at age a makes choice j in the event that such individual were to be of type k. This probability can be computed using the solution to the dynamic programming problem. Recall that from equation (4) we have $v_{3a}(x_ia,\theta_2)$ and from equation (10) we have for $d=1,2$,

$$\begin{aligned}v_{da}(x_{ia},\theta_1,\theta_2)&=u_{da}(x_{ia},\theta_2)\\&\quad+\beta\sum_{x_{a+1}}E_\varepsilon\Big[\max_{j\in\mathcal{D}(0)}\{v_{j,a+1}(x_{a+1},\theta_1,\theta_2)+\varepsilon_{j,a+1}\}\Big]f_{da}(x_{a+1}|x_{ia};\theta_1)\end{aligned}$$

and given our distributional assumptions on ε, we have the closed-form solution noted by Rust (1987):

$$E_\varepsilon\Big[\max_{j\in\mathcal{D}(0)}\{v_{j,a+1}(x_{a+1},\theta_1,\theta_2)+\varepsilon_{j,a+1}\}\Big]=\ln\Big(\sum_{j\in\mathcal{D}(0)}\exp\big(v_{j,a+1}(x_{a+1},\theta_1,\theta_2)\big)\Big). \tag{16}$$

Once $\{v_{ja}(x, \theta)\}$ is computed $\forall(j, a, x)$, we can easily compute the choice probabilities as follows:

$$\begin{aligned}\Pr(d = j|x_{ia}, k, \theta_1, \theta_2) &= \Pr\bigl(v_{ja}(x_{ia}) + \varepsilon_{ja} > v_{la}(x_{ia}) + \varepsilon_{la} \forall l \neq j, j \in \mathcal{D}(0)\bigr) \\ &= \frac{\exp\bigl(v_{ja}(x_{ia}, \theta_1, \theta_2)\bigr)}{\sum_{l \in \mathcal{D}(0)} \exp\bigl(v_{la}(x_{ia}, \theta_1, \theta_2)\bigr)}.\end{aligned} \tag{17}$$

Identification

Our model has three key features that contribute to its identification. (a) it is a finite horizon model in which we observe the last decision-making period, (b) there is a terminal action (sterilization), and (c) our preferences for children are age invariant. In addition, our parametric structure for preferences contributes further restrictions. Data on the frequency of unwanted births for each woman helps identify the unobserved heterogeneity in $\lambda_{0,k}$. Some women experience multiple unwanted births; some only experience one or two. Some have no unwanted births. A three-type structure then rationalizes the particular shape of the distribution of the number of unwanted births these women have which is different from the one that would result from a common, homogeneous, unwanted, birth probability process. The separate identification of η and μ parameters is ensured by sample variation in the probability of birth given temporary contraception, as in Carro and Mira (2006). Regarding the identification of preferences for children, the unobserved heterogeneity in preferences for the number of children ($\eta_{2,k}$) is primarily identified by the panel data on choices to pursue children and the lack of age effects in these preferences for children in our utility function. Some women are observed to pursue pregnancies multiple times whereas others are only observed to do so two or three times and yet others are never observed to pursue pregnancy or only do so once. A three unobserved type structure captures these distinct patterns of purposeful pregnancy-seeking behavior in the panel data. Regarding unobserved heterogeneity in preferences for variety ($\eta_{4,k}$), we normalize $\eta_{4,1} = 0$ to ensure representation of couples who have no preferences for particular sex composition in their offspring.[40] The parameter $\eta_{4,k}$ is then freely estimated for types 2 and 3. These are identified by the differential propensity to pursue an additional pregnancy among those who have at least one child of each sex and those who still have all of their children of the same sex. This differential propensity can be observed with a substantial sample size both at parity $n = 2$ by comparing $(n^b, n^g) = (1, 1)$ with those who have $(2, 0)$ or $(0, 2)$ and at parity $n = 3$ by comparing those with $(2, 1)$ or $(1, 2)$ with those who have either $(0, 3)$ or $(3, 0)$. The quasi-experimental variation inherent in the random determination of sex at concep-

[40]As noted in footnote 39, there appears to exist a segment of the population that cares neither about variety nor about the sex of the child/children. This group should not be interested in using the technology. But because in our model the technology is introduced in a cost-free manner, it is important to ensure these parameters that capture (lack of) preference for certain sex and/or sex composition are exactly zero rather than merely *close* to zero for this group. Only then can we be confident this group will not use the technology that is not interested in using. Noisily estimated small departures from exactly zero preference for variety in that unobserved type would unrealistically induce this unobserved type to use the technology, too, as long as it is free. Similar reasoning leads us to normalize $\eta_{5,1} = 0$.

tion together with lack of access to sex-selection technology helps in the identification of $\eta_{4,k}$. Intuitively, when the preference parameter associated with sex variety (η_4) is zero, there should be no differential propensity to pursue an intended third pregnancy among the couples who have and those who have not reached variety in the sex of their offspring. But as η_4 becomes more and more positive, this differential increases monotonically. Data on pregnancy intention helps by purging unintended third births from this critical implicit moment used for identification.[41] Similar arguments can be made about the unobserved heterogeneity in the parameter ($\eta_{5,k}$), which captures possible bias in favor of boys or girls. Differential propensity to pursue pregnancies after only having boys or girls contributes to identification of this parameter.

Parameter estimates

Tables 4 and 5 present the maximum likelihood estimates for the structural parameters. As can be seen in the first of these tables, $\eta_{2,k}$ is significant for all types. It is negative for type 1, positive and moderately sized for type 2, and positive and large for type 3. These parameters explain our findings later shown in Table 9, that type 1 tends to remain childless or have only one child, type 2 tends to have either 2 or 3 children, while type 3 tends to be the most prolific. Turning to the parameter capturing preference for variety, $\eta_{4,2}$ is positive and significant, implying that attaining variety in the sex of the offspring provides a substantial boost to the utility of type 2. On the other hand, the estimate for $\eta_{4,3}$ is small, negative, and not statistically significant.

$\eta_{5,2}$ and $\eta_{5,3}$ are both negative implying that girls are preferred to boys for both types 2 and 3 but the effects is larger and only statistically significant for type 2. The parameters μ capture a relatively small cost of temporary contraception μ_2 and a larger utility cost from permanent contraception μ_3.

In Table 5, we see that the parameters λ, characterizing the probability of an unintended birth next period conditional on engaging in temporary contraception this period imply that this probability declines strongly with age. The unobserved types have quite different intercepts λ_0, with type 1 and type 3 having much lower and higher probabilities of experiencing unwanted pregnancies than type 2. Preferences for children and tendency to experience unwanted pregnancies are thus positively correlated across types. The parameters δ, characterizing the unobserved type probability distribution imply that those who tend to marry relatively late are more likely to be type 1. Couples of type 1 are very unlikely to have unwanted children and they also do not derive much utility from having children so the few children they do have are primarily associated with unwanted pregnancies or large utility shocks ε_1 to the utility of pursuing pregnancy in a given period.

Using the estimated δ and the distribution of initial condition, we can estimate the prevalence of unobserved types in this population. Table 6 reports the distribution of types, unconditionally and broken down by education group. Type 2 is the most preva-

[41]As noted by Rosenzweig and Wolpin (1993), pregnancy intention reports may contain measurement error. We take these reports at face value and view our ability to model unintended births as an advantage of our approach. Assuming all pregnancies were intended may create other, potentially larger issues for identification and estimation.

Table 4. Structural parameter estimates—preferences for children and choice-specific utility costs.

		Estimate	S.E.
Utility from Children			
$\overline{u}_k = \eta_1 + \eta_{2,k} n_a + \eta_3 n_a^2 + \eta_{4,k} I\{n_a^g \geq 1 \cap n_a^b \geq 1\} + \eta_{5,k} I\{n_a^b \geq 1\} + \sum_{q=1}^{3} \gamma_q I_{q,a} e$			
At least one child	η_1	0.052	0.014
Number of Children (Type 1)	$\eta_{2,1}$	−0.080	0.015
Number of Children (Type 2)	$\eta_{2,2}$	0.124	0.012
Number of Children (Type 3)	$\eta_{2,3}$	0.423	0.021
Number of Children^2	η_3	−0.054	0.002
Taste for Variety (Type 1)	$\eta_{4,1}$	0	–
Taste for Variety (Type 2)	$\eta_{4,2}$	0.106	0.011
Taste for Variety (Type 3)	$\eta_{4,3}$	−0.020	0.049
Preference for Boys (Type 1)	$\eta_{5,1}$	0	–
Preference for Boys (Type 2)	$\eta_{5,2}$	−0.037	0.010
Preference for Boys (Type 3)	$\eta_{5,3}$	−0.001	0.058
At least one child × High Edu	γ_1	−0.091	0.011
At least two children × High Edu	γ_2	0.067	0.009
3 or More children × High Edu	γ_3	−0.056	0.005
Choice-Specific Utilities			
Cost of No Contraception	μ_1	0	–
Cost of Temporary Contraception	μ_2	−0.045	0.009
Cost of Permanent Contraception	μ_3	−3.098	0.113
Cost of Permanent Contraception × High Edu	μ_1^h	−0.640	0.074

Note: Standard errors computed using the square root of the diagonal of the inverse of the Hessian. $\eta_{4,1}$, $\eta_{5,1}$, and μ_1 normalized to zero.

lent one, comprising about 80% of this population. Type 1 accounts for another 15% whereas the remaining 5% are of type 3. While type 2 is clearly the most prevalent for both education groups, conditional on being in the high education group, a woman is somewhat more likely to be of type 1. Similarly, in Table 7 we report the distribution of types for those who marry early (age at marriage below the median) and those who marry late (age at marriage above the median). Women who marry late belong in couples that are less likely to be of types 2 and 3 and more likely to be of type 1.

Model fit

To ascertain how well the model estimated by maximum likelihood fits some key patterns in the NSFG data we simulate fertility histories by drawing shocks and applying the policy functions derived from the solution to the dynamic programming model at the estimated parameters.

We first compare simulated fertility to actual fertility by the time of interview in the NSFG data.[42] Table 8 presents the results. The model does a relatively good job at match-

[42]To construct simulated fertility by the time of history, we simulate the histories up until the age at which the empirical counterpart of the simulated person had the NSFG interview.

TABLE 5. Structural parameter estimates—probability of unintended pregnancy and unobserved types.

		Estimate	S.E.
	Transition Probability		
	$\Pr(n_{a+1} = n_a + 1 \mid d = 2, a, e, k) = \frac{\exp(\varsigma_k)}{1+\exp(\varsigma_k)}$		
	$\varsigma_k = \lambda_{0,k} + \lambda_1 \tilde{a} + \lambda_2 \tilde{a}^2 + \lambda_3 \tilde{a}^3 + \lambda_4 e$		
	$\tilde{a} = \frac{a-14}{30}$		
Constant (Type 1)	$\lambda_{0,1}$	−2.404	0.389
Constant (Type 2)	$\lambda_{0,2}$	0.157	0.159
Constant (Type 3)	$\lambda_{0,3}$	0.728	0.177
Age	λ_1	−16.758	1.403
Age Squared	λ_2	30.790	3.705
Age Cubic	λ_3	−21.671	2.980
High Education	λ_4	−0.058	0.040
	Unobserved Types Probabilities		
	$\Pr(type = k) = \frac{\exp(\xi_k)}{\sum_{j=1}^{3} \exp(\xi_j)}$		
	$\xi_k = \delta_{0,k} + \delta_{1,k} \frac{A-14}{30} + \delta_{2,k} (\frac{A-14}{30})^2 + \delta_{3,k} e$		
Constant (Type 2)	$\delta_{0,2}$	3.333	0.275
Age at Marriage (Type 2)	$\delta_{1,2}$	−4.581	1.494
Age at Marriage Squared (Type 2)	$\delta_{2,2}$	−1.322	1.814
High Education (Type 2)	$\delta_{3,2}$	0.045	0.162
Constant (Type 3)	$\delta_{0,3}$	2.167	0.384
Age at Marriage (Type 3)	$\delta_{1,3}$	−13.708	2.588
Age at Marriage Squared (Type 3)	$\delta_{2,3}$	5.447	4.228
High Education (Type 3)	$\delta_{3,3}$	0.244	0.233

Note: Standard errors computed using the square root of the diagonal of the inverse of the Hessian. $\delta_{0,0}$, $\delta_{0,1}$, $\delta_{0,2}$ and $\delta_{0,3}$ normalized to zero. Age and Age at Marriage are normalized by substracting 14 and dividing by 30.

ing the broad patterns of completed fertility by the time of interview ($n^b_{A_i^{nsgg}} + n^g_{A_i^{nsgg}}$) although it underestimates the percent childless.

Figure 3 presents additional evidence on model fit.[43] As can be seen in Figure 3a, the model does a great job at matching sex-specific completed fertility by the time of interview. Also, while not our main focus, the model does a relatively good job at matching a critical measure of fertility timing: the distribution of age at first birth among NSFG

TABLE 6. Prevalence of unobserved types by education.

	All	Low Edu	High Edu
Type 1	14.9%	11.1%	17.2%
Type 2	80.1%	82.8%	78.6%
Type 3	4.9%	6.1%	4.2%

[43] Figures A.1 and A.2 in the Appendix of the Online Supplementary Material (Li and Pantano (2023)) present model fit figures similar to Figure 3, but separately by education group.

Table 7. Prevalence of unobserved types by age at marriage.

	All	Early	Late
Type 1	14.9%	7.6%	23.2%
Type 2	80.1%	85.2%	74.3%
Type 3	4.9%	7.1%	2.4%

women who have had at least one birth by the time of interview. Figure 3b presents the results. In addition, and despite its parsimony, the model captures the broad patterns of fertility behavior by age. Figures 3c to 3f present the results. Figure 3c shows the percentage of women who have been sterilized by a particular age and, therefore, no longer have an opportunity to make choices. Figures 3d and 3e show the percentage of all married women who are either pursuing pregnancies or temporarily contracepting at each age. The model captures the smooth decline in the percent of couples pursuing intended pregnancies as married women become older and the corresponding age profile in the percent who engage in reversible forms of contraception. Figure 3f shows that our model for contraceptive failure captures the data on unwanted births by age very well. Figures 3g and 3h show model fit for the probability of eventually (by the time of interview) having an unwanted or wanted birth conditional on various configurations of the sex mix of existing children (n^b, n^g). Figure 3g shows that our model reproduces the fact that, for lower parities (0, 1, and 2), the experiencing of an unwanted pregnancy is somewhat unrelated to the sex mix of existing children.[44] Figure 3h shows that the model is successful at capturing that women are much more likely to voluntarily continue fertility when they are childless or only have had one child, and that when having 2 children they are more likely to continue fertility when they have not yet reached sex variety in their offspring $((n^b, n^g) = (2, 0)$ or $(n^b, n^g) = (0, 2))$ than when they have $((n^b, n^g) = (1, 1))$. While the model does not capture behavior exactly at every single year of age, we feel it captures the broad age trends present in the data. While it could be possible to match

Table 8. Model fit—completed fertility by the time of interview.

	Data	Model
0	17.9%	15.1%
1	20.3%	21.8%
2	38.8%	38.5%
3	16.6%	18.2%
4	4.7%	4.3%
≥5	1.7%	2.1%

Note: Sample rertricted to fertile married women 25 and older at time of interview. Pooled samples from NSFG waves 1982–2008.

[44] The model does not perfectly capture some data moments at higher parities that are based on less observations, such as the percent who go on to experience an unwanted pregnancy after having 4 boys and no girls or 4 girls and no boys.

even better by introducing age effects in the utility function, we feel the more parsimonious model with age-invariant preferences is preferable.[45]

6. Counterfactual experiment: Sex-selection technology

A widely available, easily affordable, morally sound sex-selection technology would presumably allow couples to more precisely target their desired sex mix. In particular, fertility could be reduced if parents need fewer attempts to achieve sex variety in their offspring. On the other hand, this very same technology could increase fertility by reducing the sex uncertainty about the child that is to be conceived. One could imagine some parents who currently settle for only one child, but would be more than happy to have two if it was guaranteed that the second child would "balance" their families. It is likely that both effects are at play. Moreover, many parents who currently have just two boys or just two girls would presumably switch to having one and one. Ultimately, it is an empirical question whether the overall impact on completed fertility would be positive or negative.

To answer the question, we resolve the dynamic optimization problem using the estimated parameters $\widehat{\theta}$, but now allowing for an expanded choice set that makes use of sex-selection technology. In particular, we now let choice $d = 1$ in the original model to be characterized by two options $(1b, 1g)$, capturing whether a boy or a girl is sought when pursuing pregnancy:[46]

$$d_a = \begin{cases} 1 \text{ if pursue pregnancy} = \begin{cases} 1b \text{ if pursue a boy,} \\ 1g \text{ if pursue a girl,} \end{cases} \\ 2 \text{ if temporary contraception,} \\ 3 \text{ if sterilize,} \end{cases} \tag{18}$$

where the alternative-specific value function associated with having a birth $j = 1$ is now given by

$$v_1(x_a) = \max\bigl[v_{1b}(x_a); v_{1g}(x_a)\bigr] \tag{19}$$

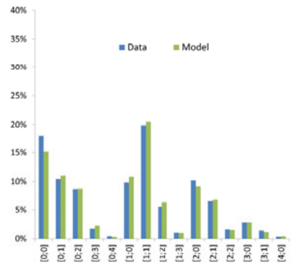
and where the alternative-specific value associated with having a boy or a girl is given by

$$v_{1b}(x_a) = u_1(x_a) + \beta E_\varepsilon\Bigl[\max_{j\in\mathcal{D}(0)}\bigl\{v_{j,a+1}\bigl(n_a^g, n_a^b + 1, e\bigr) + \varepsilon_{j,a+1}\bigr\}\Bigr], \tag{20}$$

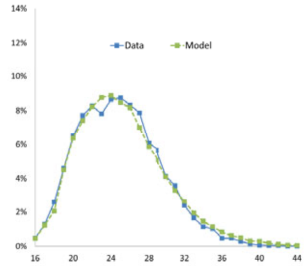
$$v_{1g}(x_a) = u_1(x_a) + \beta E_\varepsilon\Bigl[\max_{j\in\mathcal{D}(0)}\bigl\{v_{j,a+1}\bigl(n_a^g + 1, n_a^b, e\bigr) + \varepsilon_{j,a+1}\bigr\}\Bigr]. \tag{21}$$

[45]When interpreting these graphs, note that since we are only looking at histories of married couples beginning with the woman's age at marriage, the set of couples making choices changes at each age. Therefore, these patterns do not represent the choice behavior from 15 to 43 for any particular cohort. These figures show for our sample based on histories of married couples, what percent of women, at any given age, had already sterilized and what percent chose each of the two other alternatives.

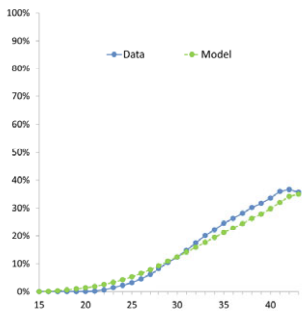
[46]Consistent with our focus on technologies that aid sex selection before fertilization, when pregnancy is unintended (i.e., it results from contraceptive failure after choice $d = 2$), we continue to assume that sex determination is random.



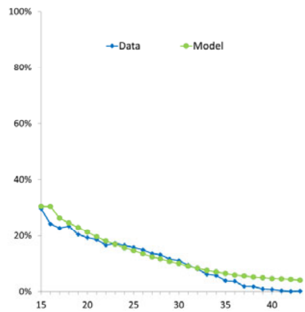
(a) Completed fertility by interview



(b) Age at first birth

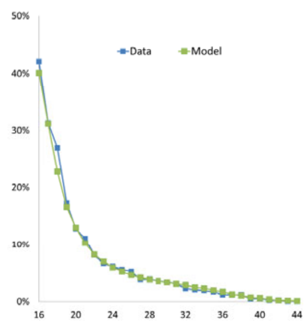


(c) % ever sterilized by age

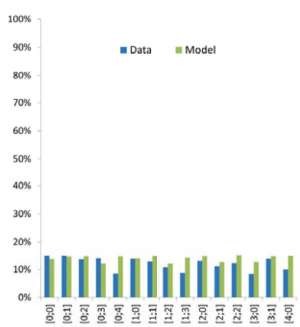


(d) % pursuing pregnancies by age

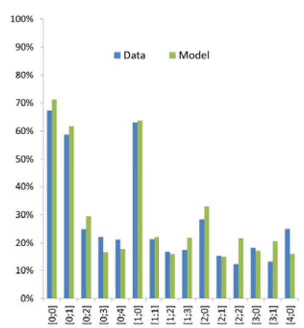
(e) % temp. contraception by age



(f) Pr(`Unwanted Birth|a,j=2`)



(g) % unwanted pregnancies by sex mix



(h) % wanted pregnancies by sex mix

Figure 3. Model fit.

After solving this expanded model, we derive new policy functions and simulate fertility histories (under the same history of shocks used for the Baseline simulation). Since here we are no longer concerned with how well the model fits, the NSFG data, we generate complete fertility histories from age at marriage all the way up to age 44 for all simulated women. We do this both in the baseline and counterfactual simulations.[47] Once we obtain the new simulated histories, we explore what happens to overall fertility. Note that we keep the same stochastic structure for preference shocks used in estimation. Namely, we only have alternative-specific shocks to the utility of the three original alternatives and do not introduce sex-specific preference shocks to the utility from pursuing a sex-specific pregnancy. Again, given that the model is estimated on data assumed to have been generated under a regime in which sex-selection opportunities are not available, the proper structural interpretation of ε_{1a} is that of an unobserved taste shifter that makes having a birth at age a, *whatever its sex*, a particularly good idea. Moreover, introducing a fourth shock would distort the value functions as the maximum over four realizations of ε is of course larger than the maximum over three, and this extra source of utility would be over and above the one generated by the fact that $v_1(x_a) = \max[v_{1b}(x_a); v_{1g}(x_a)]$ instead of $v_1(x_a) = 0.488v_{1b}(x_a) + 0.512v_{1g}(x_a)$.

To begin, we first explore the impact on overall completed fertility for a given cohort.[48] We focus on a steady-state comparison in the sense that, in both cases, baseline and counterfactual, these women are exposed to alternative regimes from their ages at marriage onward. The steady-state impact on a cohort's completed fertility is quite different from the short-run impact of technology introduction. In the short run, the new technology is introduced at different stages in the life cycle for different cohorts. Women who are older when the technology is introduced will have less of an opportunity to modify their fertility plans as much of their fertility has occurred already. This consideration also highlights the usefulness of our approach. Even if we can randomly assign technology access to a treatment and control group, we would then need to wait $(44 - 15 =)$ 29 years to observe completed fertility for both groups and assess the experimental impact.[49] Table 9 presents the results.

As can be seen in the table, comparing the first columns of the baseline and counterfactual panels, there is a decline of approximately 2 percentage points in the share of couples who have 3 children and an increase of 4 percentage points in the share that has only two children. This is primarily driven by the behavior of the more prevalent type (Type 2). As can be seen in columns 5 and 6 for each panel, these changes are similar for both education groups. A takeaway message from Table 9 is that the net impact of this technology on a cohort's completed fertility turns out to be only slightly negative. In the last row of Table 9, we compute the average number of children a representative

[47] The distribution of age at marriage in the sample overrepresents early marriages due to NSFG histories being censored at the time of interview when many women ages 15–44 are still single. To address this, we estimate a duration model for time to first marriage accounting for such censoring and then draw ages at marriage from the correct distribution to endow the simulated women with their initial condition.

[48] We are assuming there are no nonpecuniary or psychic costs of using the new technologies.

[49] Since we do not model marriage decisions, we do not consider the impact of sex-selection technology on the distribution of age at marriage. We also do not model nor consider out-of-wedlock fertility.

Table 9. Steady-state impact of sex-selection technology on completed fertility.

	Baseline						Counterfactual					
	All	Type I	Type II	Type III	Low Edu	High Edu	All	Type I	Type II	Type III	Low Edu	High Edu
Childless	8%	45%	0%	0%	3%	11%	8%	45%	0%	0%	3%	11%
1 Child	10%	42%	2%	0%	12%	8%	9%	42%	2%	0%	11%	8%
2 Children	42%	14%	51%	0%	32%	47%	46%	14%	56%	0%	37%	51%
3 Children	30%	0%	39%	3%	38%	27%	28%	0%	36%	3%	35%	24%
4 Children	6%	0%	7%	29%	10%	5%	6%	0%	6%	28%	8%	4%
5+ Children	3%	0%	1%	68%	6%	2%	3%	0%	1%	68%	5%	2%
Avg. Children	2.28	0.69	2.51	4.87	2.58	2.12	2.24	0.69	2.47	4.88	2.54	2.09

Note: Numbers in each column show the distribution of completed fertility. These numbers add up to 100%. These are steady state distributions in the sense that women either have (counterfactual) or do not have (baseline) access to the technology since the time of marriage. The same set of age-specific shocks to preferences and contraceptive failure as well as implicit sex-determination shocks by parity are used in both baseline and counterfactual simulations. Avg. number of children computed assuming families with five or more children have only 5 children.

married couple will have. In contrast to previous findings, we see that the average family size only declines by 1.8%, from 2.28 children at baseline to 2.24 in the counterfactual. While this is not particularly sizable when viewed against a no-effect benchmark, it is quite different from what one would obtain using a purely demographic approach. The net fertility effect of $(2.241 - 2.277 =) - 0.036$ is small but statistically different from zero.[50] The second, third, and fourth columns of each panel show the results separately by unobserved type. Couples of type 1 tend to have few children, while couples of type 3 tend to have many. Type 2 couples, the most prevalent type, tend to have either 2 or 3 children. Of course, couples of type 1 (15% of this population) are not affected in the counterfactual as they are assumed not to care about offspring sex and, therefore, do not take advantage of the opportunities given by the new technology. Our aggregate results are then driven by couples of type 2 as type 3 represents a small minority for this population. These results highlight the importance of allowing for unobserved heterogeneity in preferences, not only in how the number of children a couple has affects their utility but also about how important offspring sex composition is and how heterogeneity in these dimensions is correlated across our three unobserved types.

Table 9 provides a first snapshot of the likely effects but masks substantial changes that might occur in sex composition without necessarily changing parity. Table 10 presents a more detailed picture of the impact of sex-selection technology by looking at what happens to *sex-specific* completed fertility.

The first obvious pattern that emerges from the table in column 4 is that since preferences for variety for the largest type ($\eta_{4,2}$) are positive and sizable, multichild sex-unbalanced sibships $(n^b, n^g) = (2, 0), (0, 2), (3, 0), (0, 3), (4, 0)$, and $(0, 4)$ all have very low incidence in the counterfactual scenario as there is a "flight to sex variety." This is partly a result of the fact that we are not allowing for any nonpecuniary, nor pecuniary costs of using the technology. In that sense, this counterfactual is only relevant in a world in which psychic and monetary obstacles for widespread use have been completely removed.[51] As expected, parents with one boy and one girl $(n^b, n^g) = (1, 1)$ become the overwhelming majority: the share of couples with this particular sex composition in their completed fertility soars from 24% to 43%. At the same time, the percentage with either two boys or two girls declines from 9% to just 1 or 2%. Finally, as can be seen at the bottom of the table, there is a change in the male-to-female sex ratio, which declines from 1.05 to 0.83 as couples tend to have more girls given $\eta_{5,k} < 0$ for $k = 2, 3$.

The technology does not substantially alter the distribution of age at first birth. Figure 4 shows that the baseline and counterfactual distributions are almost identical.

[50] To assess the statistical precision of this small effect, we took 400 draws from the estimated asymptotic distribution of the structural parameters, using our estimated variance-covariance matrix and recomputed total fertility under baseline and counterfactual scenarios as well as their difference, which captures the net effect of the technology. A 95% confidence interval for the net fertility effect of the policy is $(-0.045, -0.028)$. While the interval does not include zero, it does suggest a precisely estimated small effect.

[51] In any event, since our data comes from a regime in which the technology is not available, we cannot directly identify those who would use/not use this technology at each price. Extending the model to incorporate labor supply could help identify the willingness to pay for this technology. Still, it would be impossible (in the absence of richer data) to identify those who would not use the technology on bioethical grounds.

We also observe a small impact on sterilization. Figure 5 shows the baseline and the slightly higher counterfactual % of women ever sterilized by each age.

An even more informative way to explore the impact of this technology is to tabulate the resulting distribution of completed fertility, n under the counterfactual regime

TABLE 10. Steady-state impact of sex-selection technology on sex-specific completed fertility.

	Baseline			Counterfactual		
	All	Low Edu	High Edu	All	Low Edu	High Edu
$(n^b, n^g) = (0, 0)$	8%	3%	11%	8%	3%	11%
$(n^b, n^g) = (0, 1)$	5%	6%	4%	5%	6%	4%
$(n^b, n^g) = (0, 2)$	9%	7%	10%	2%	2%	2%
$(n^b, n^g) = (0, 3)$	4%	4%	3%	0%	0%	0%
$(n^b, n^g) = (0, 4)$	0%	1%	0%	1%	1%	1%
$(n^b, n^g) = (1, 0)$	5%	6%	4%	4%	5%	4%
$(n^b, n^g) = (1, 1)$	24%	19%	26%	43%	34%	47%
$(n^b, n^g) = (1, 2)$	10%	13%	9%	14%	19%	12%
$(n^b, n^g) = (1, 3)$	1%	2%	1%	1%	2%	1%
$(n^b, n^g) = (2, 0)$	9%	6%	10%	1%	1%	1%
$(n^b, n^g) = (2, 1)$	12%	14%	10%	13%	16%	11%
$(n^b, n^g) = (2, 2)$	2%	3%	2%	2%	4%	1%
$(n^b, n^g) = (3, 0)$	5%	5%	4%	0%	0%	0%
$(n^b, n^g) = (3, 1)$	2%	3%	1%	1%	2%	1%
$(n^b, n^g) = (4, 0)$	1%	1%	0%	0%	0%	0%
Other (5+)	3%	6%	2%	3%	5%	2%
Avg. Number of Boys	1.17	1.32	1.09	1.02	1.14	0.95
Avg. Number of Girls	1.11	1.26	1.03	1.22	1.40	1.13
Sex-Ratio	1.05	1.05	1.05	0.83	0.81	0.84

Note: Sex ratio is computed as average number of boys divided by average number of girls.

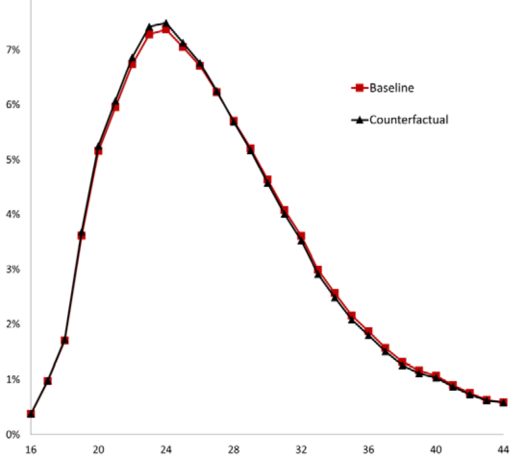


FIGURE 4. Distribution of age at first birth—baseline and counterfactual.

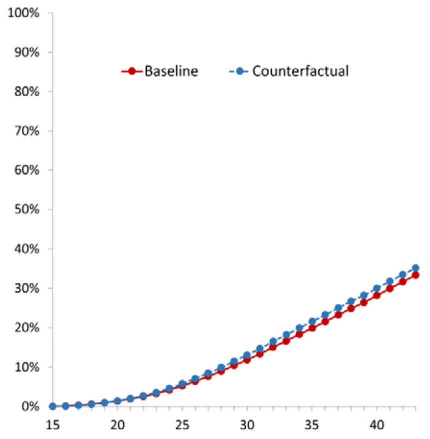


FIGURE 5. % ever sterilized by age—baseline and counterfactual.

with sex selection, for each given completed fertility at baseline.[52] Table 11 presents the results. Each row gives the counterfactual distribution of completed fertility for a given level of completed fertility at baseline. For example, the third row tells us what happens in the counterfactual to those couples who had three children in the baseline scenario without sex-selection technology: no one becomes childless, 16% ends up having two, 82% remains with three, and 1% increases to four.

The decomposition shows several interesting results. First, note that, as expected, no one becomes childless because of this technology. More interestingly, note that even though many couples who had three or four children in the baseline would reduce their fertility in the counterfactual scenario, as they are able to reach variety among their offspring with fewer attempts, there is a nonnegligible *increase* in fertility among families that only have one or two children at baseline: 5% of families that used to have only

TABLE 11. Decomposition of completed fertility.

		Counterfactual					
		0	1	2	3	4	5+
Baseline	0	99%	0%	0%	0%	0%	0%
	1	0%	94%	5%	1%	0%	0%
	2	0%	0%	96%	4%	0%	0%
	3	0%	0%	16%	82%	1%	0%
	4	0%	0%	4%	15%	80%	1%
	5+	0%	0%	1%	0%	3%	96%

Note: Numbers in each row show the the counterfactual distribution of completed fertility for a given completed fertility at baseline. These numbers add up to 100%. The same set of age-specific shocks to preferences and contraceptive failure and implicit sex-determination shocks by parity are used in both baseline and counterfactual simulations.

[52]During both the baseline and counterfactual simulations, we use the same set of shocks to preferences and contraceptive failure shocks by age and the same set of implicit sex-determination shocks at conception by parity.

one child, would now have 2. Similarly, 4% of families that used to have two will now have three. A vast majority (96%) of those with two children at baseline ($n^g + n^b = 2$) remains with two children in the counterfactual. This last result masks important changes though. From the previous tables, we know that very few ends up with $(0, 2)$ or $(2, 0)$ in the counterfactual so many couples are taking advantage of the technology to pick the sex of their two children. Table 9 provides even deeper insight into the wide-ranging changes that would be brought about by the availability of sex-selection technology. Table 12 is similar to Table 11 but for baseline-counterfactual transitions in *sex-specific* completed fertility as opposed to *overall* completed fertility.

The column associated with $(n^b, n^g) = (1, 1)$ in the counterfactual is the most populated, meaning almost every configuration at baseline (actually all of them except the families contained in the childless category $(0, 0)$) "exports" some couples to $(n^b, n^g) = (1, 1)$ in the counterfactual. In addition to those who already had $(1, 1)$ at baseline, the major contributing configurations are $(0, 2)$ and $(2, 0)$, with 80% and 89% of their baseline women, respectively, now having $(1, 1)$ once sex-selection technology is introduced. Also, 22% of those with $(0, 3)$ and 34% of those with $(3, 0)$ at baseline now end up with $(1, 1)$ in the counterfactual scenario. These are the women who took their chances to reach variety and failed. The realistic timing of the model setup, as well as its stochastic structure, generates more subtle changes, which would be less obvious a priori. For example, not all of those with $(1, 1)$ at baseline remain with $(1, 1)$ in the counterfactual. This is most likely due to the fact that the policy function for pursuing fertility is different for the types that take advantage of the new technology. This induces changes in the optimal timing of births. The size of the preference shock needed to pursue pregnancy changes once sex-selection opportunities are available.

While we are not able to compute explicit welfare gains, Table 12 portrays a potentially large increase in welfare, evidenced by the large number of couples who change their fertility behavior under the new technology. Of course, we know welfare will increase as women have an additional option, but what is striking is how widespread the effects turn out to be. Many couples are affected. Some of them increase their fertility, some of them decrease it, and some of them stay at the same parity yet adjust the sex mix in their offspring. Each and every one of these changes involves a potentially large welfare gain.

The analysis so far has explored steady-state implications. That is, we asked what demographic behavior would look like in a new steady state where all cohorts have access to this technology from the beginning of their reproductive careers. Another advantage of our approach is that it allows us to explore the transitional dynamics until the new steady state is reached. Figure 6 shows how the total fertility rate for ever-married women evolves between the old and new steady states.[53] Perhaps surprisingly, there is no noticeable uptick in fertility during the first year of the policy. While older women who had completed their fertility may take advantage of the newly available technology and add to their number of children, the new policy function for women who are

[53]We compute the TFR for ever-married women in a given year as the sum of age-specific probabilities that an ever-married woman of that age has a child in that year.

TABLE 12. Decomposition of sex-specific completed fertility.

		Counterfactual (n^b, n^g)															
		(0, 0)	(0, 1)	(0, 2)	(0, 3)	(0, 4)	(1, 0)	(1, 1)	(1, 2)	(1, 3)	(2, 0)	(2, 1)	(2, 2)	(3, 0)	(3, 1)	(4, 0)	5+
Baseline (n^b, n^g)	(0, 0)	99%															
	(0, 1)		92%					6%	1%			1%					
	(0, 2)			15%				80%	4%			1%					
	(0, 3)				4%			22%	72%	1%			1%				
	(0, 4)					19%		5%	24%	49%							4%
	(1, 0)		12%				85%	3%									
	(1, 1)			3%				93%	3%			1%					
	(1, 2)				2%			9%	64%	1%		24%	1%				
	(1, 3)					18%		3%	9%	40%		2%	27%				1%
	(2, 0)							89%	1%		8%	2%					
	(2, 1)							14%	30%			54%	1%				
	(2, 2)					16%		3%	3%	17%		2%	49%		9%	1%	1%
	(3, 0)							34%				65%		1%			
	(3, 1)					12%		5%	4%	2%		14%	33%		29%	1%	1%
	(4, 0)					7%		7%		1%		37%	1%		42%	2%	2%
	5+							1%					1%		1%		97%

Note: Numbers in each row show the counterfactual distribution of sex-specific completed fertility for each given sex-specific completed fertility configuration at baseline. These numbers add up to 100%. The same set of age-specific shocks to preferences and contraceptive failure and implicit sex-determination shocks by parity are used in both baseline and counterfactual simulations.

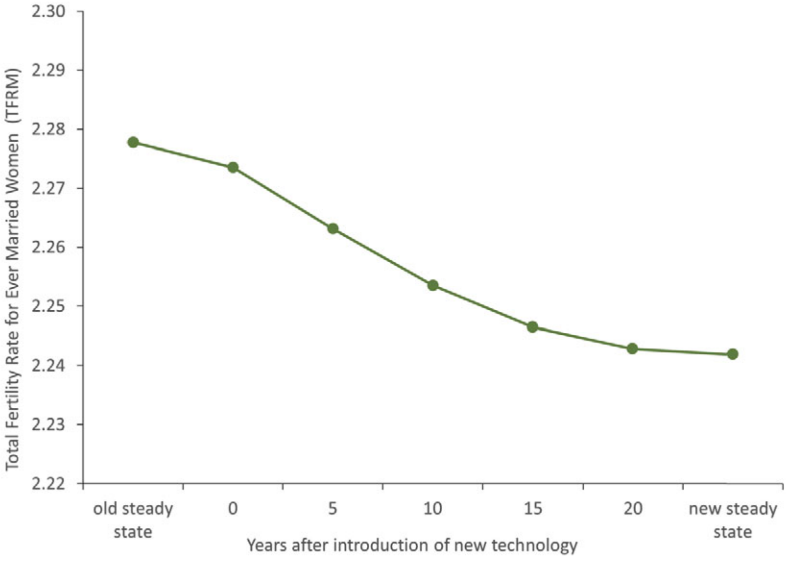


FIGURE 6. Transitional dynamics—total fertility rate for ever married women.

younger at the time the new technology becomes available outweighs this effect, and on net there is a slight decline during that first year. As time goes by and the effect for older women dissipates as they age out of their reproductive time windows, the economy converges smoothly to a new steady state with a permanently lower TFR. It should be emphasized though, that this lower TFR in the new steady state is still much higher than what one would predict using alternative methods that only factor in the fact that couples could reach their preferred number and sex-composition with fewer attempts.

Finally, we ask a question of more empirical relevance. We can examine what would happen if this technology increased the chances of having a child of a given sex but was not 100% accurate. Moreover, we could ask what would happen when accuracy differs by sex. For example, we can ask what if, as in MicroSort's case, accuracy differs by sex, with 90% accuracy when seeking a girl and 75% accuracy when seeking a boy. This differential accuracy translates into an asymmetry in effective access. Table 13 presents the results.

As can be seen in the table, differential technology accuracy by sex now leads to a steady- state reduction in the sex ratio from 1.05 to 0.71, with 1.41 girls for each boy. This results from the combination of three mechanisms. First, among all parents using the technology to select the sex of their child, the success rate is higher among those seeking girls. So, mechanically, more girls are born. Second, types 2 and 3 do have a small and in the case of type 2, nonnegligible, preference for girls, which leads to more girls in the counterfactual. Finally, there is another force that should increase the number of girls. While most couples seeking a girl are likely to be undeterred by the 10% failure rate, that is not the case for those seeking a boy. Couples who wish to have a boy face only a 75% success rate and this might not be enough for some of them to take the risk.

Moreover, differential accuracy could potentially induce many couples that seek variety to attempt boys at their first birth, as they are technologically more difficult to obtain and it can be shown that in the absence of preferences for boys versus girls it would

Table 13. Steady-state impact of sex-selection technology on sex-specific completed fertility with differential accuracy by sex success rates: 75% for boys, 90% for girls.

	Baseline			Counterfactual		
	All	Low Edu	High Edu	All	Low Edu	High Edu
$(n^b, n^g) = (0, 0)$	8%	3%	11%	8%	3%	11%
$(n^b, n^g) = (0, 1)$	5%	6%	4%	5%	7%	5%
$(n^b, n^g) = (0, 2)$	9%	7%	10%	8%	6%	9%
$(n^b, n^g) = (0, 3)$	4%	4%	3%	3%	3%	2%
$(n^b, n^g) = (0, 4)$	0%	1%	0%	1%	1%	1%
$(n^b, n^g) = (1, 0)$	5%	6%	4%	4%	5%	4%
$(n^b, n^g) = (1, 1)$	24%	19%	26%	34%	28%	38%
$(n^b, n^g) = (1, 2)$	10%	13%	9%	16%	20%	14%
$(n^b, n^g) = (1, 3)$	1%	2%	1%	2%	3%	1%
$(n^b, n^g) = (2, 0)$	9%	6%	10%	1%	1%	1%
$(n^b, n^g) = (2, 1)$	12%	14%	10%	11%	14%	9%
$(n^b, n^g) = (2, 2)$	2%	3%	2%	2%	4%	1%
$(n^b, n^g) = (3, 0)$	5%	5%	4%	0%	0%	0%
$(n^b, n^g) = (3, 1)$	2%	3%	1%	1%	2%	1%
$(n^b, n^g) = (4, 0)$	1%	1%	0%	0%	0%	0%
other (5+)	3%	6%	2%	3%	5%	2%
Avg. Number of Boys	1.17	1.32	1.09	0.94	1.07	0.87
Avg. Number of Girls	1.11	1.26	1.03	1.33	1.49	1.24
Sex-Ratio	1.05	1.05	1.05	0.71	0.71	0.70

Note: Numbers in each column show the distribution of sex-specific completed fertility. These numbers add up to 100%. Same set of age specific shocks to preferences and contraceptive failure and implicit sex-determination shocks by parity are used in both baseline and counterfactual simulations. Avg. number of boys and girls computed only among families with four or less children. Sex ratio is computed as average number of boys divided by average number of girls.

be optimal to first attempting what is more difficult to obtain. This would induce a gender gap in birth order, as more boys would then become firstborns. Sex-ratio imbalances among firstborns could be of potential concern, given the large literature documenting birth-order effects in a variety of life-cycle outcomes.[54] However, this technological mechanism could be muted by the small preferences for girls that we estimate to be prevalent for variety-seeking type 2. Table 14 explores the implications for the sex ratio

Table 14. Steady-state impact of inaccurate sex-selection technology on sex ratio by birth order.

<table>
<tr><th></th><th colspan="4">Baseline</th><th colspan="4">Counterfactual</th></tr>
<tr><th></th><th>All</th><th>Type I</th><th>Type II</th><th>Type III</th><th>All</th><th>Type I</th><th>Type II</th><th>Type III</th></tr>
<tr><td>Birth Order =1</td><td colspan="4" rowspan="4">49%</td><td>80%</td><td>50%</td><td>84%</td><td>85%</td></tr>
<tr><td>Birth Order =2</td><td>40%</td><td>49%</td><td>37%</td><td>76%</td></tr>
<tr><td>Birth Order =3</td><td>48%</td><td>49%</td><td>45%</td><td>71%</td></tr>
<tr><td>Birth Order =4</td><td>57%</td><td>–</td><td>48%</td><td>67%</td></tr>
</table>

Note: Numbers in each cell show the number of girls as a share of all births for each birth order among all families and for families of each type.

[54] See, for example, Black, Devereux, and Salvanes (2005) and Hotz and Pantano (2015).

along the birth-order sequence. Each cell in the table reports the share of females among births by birth order, overall and separately for each type. The left panel reports that, as expected, when sex selection is not available, this share is approximately 49% reflecting the biological sex ratio at birth without sex-selection technology. Under the counterfactual, however, we see that among offspring in families of type 2 who value sex variety, the share of girls among firstborns soars to 84% as parents (a) prefer girls to boys and (b) are technologically very likely to succeed when seeking a girl. As a result, girls become less prevalent among second-born children for this type. The share eventually becomes more balanced at higher parities. Type 3 actually prefers to avoid variety ($\eta_{4,3} < 0$) and also prefers girls slightly ($\eta_{5,3} < 0$) so there is a higher share of girls at all birth orders for this type. There are still some boys born out of unintended pregnancies for type 3. This could again be a concern as unwanted children go on to have worse life-cycle outcomes (Lin and Pantano (2015)). Notice, though, that type 3 only represents about 5% of the population so their influence in the aggregate patterns of sex ratio across birth order is rather minimal and most of the action is primarily driven by changes in the behavior of "mainstream" type 2 at parities $n = 1, 2, 3$.

7. Conclusions

Fertility preferences in the U.S. are characterized by a strong desire to achieve sex variety in offspring. Emerging technologies might soon put sex-selection opportunities within the reach of average American households. Beyond important bioethical considerations, it is important to gauge what the demographic impact of these technologies could be. In this paper, we complement traditional demographic approaches to this question by formulating a dynamic programming model of sequential fertility decisions that explicitly allows for preferences for sex variety. The traditional approach involves positing a particular set of fertility goals and the assumption that couples without access to sex selection will insist on reaching that goal no matter how costly reaching that objective turns out to be. Not surprisingly, simulating the introduction of sex-selection opportunities within this framework invariably results in large declines in family size. Instead, our approach allows parents to endogenously decide whether to pursue additional pregnancies with no preset goal other than expected lifetime utility maximization. Additionally, we do not posit, but rather identify a particular preference structure from couples' fertility behavior in a regime characterized by the absence of sex-selection opportunities. Instead of an impediment for policy evaluation, we argue that our couples' lack of exposure to sex-selection technology, supplemented by the random determination of sex at fertilization provides a critical source of identification for the structural parameter characterizing preferences for a mixed sex composition in offspring.

We estimate the model via maximum likelihood using microdata from the National Survey of Family Growth and allowing for unobserved heterogeneity in preferences for family size and sex-balance in offspring. Despite model parsimony, the model replicates fairly well some key features of the NSFG data, such as the patterns of family size and the offspring's sex composition by the time of interview as well as the distribution of age at first birth. Our results suggest that a widely available, morally acceptable, and easily affordable sex-selection technology would reduce the average family size by less than 2% in the steady state. This contrasts with a more standard demographic approach that would predict larger aggregate *reductions* in total family size. This net effect involves several changes for different married couples, with some increasing, some decreasing their completed fertility, and some keeping the same family size but adjusting the sex mix in their offspring. In the simulations, many couples are induced to change their fertility behavior upon the introduction of this technology, implying large potential gains in welfare. We also show that while a large part of the impact of the new technology is due to a large share of couples avail themselves of the technology while seeking variety in the sex of their offspring, we do find a smaller preference for girls that ends up affecting the sex ratio in the aggregate and especially among firstborns. This could be worrisome for the prospects of boys, given the large literature on birth-order effects that documents higher achievement among first-born children.

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Co-editor Peter Arcidiacono handled this manuscript.

Manuscript received 5 February, 2022; final version accepted 26 May, 2022; available online 17 June, 2022.