The Demographic Consequences of Gender Selection Technology*

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PRELIMINARY

Abstract

Over the last several years highly accurate methods of gender selection before conception have been developed. Given that strong preferences for gender variety in offspring have been documented for the U.S. we move beyond bio-ethical and moral considerations and ask what the demographic consequences of gender 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 from the National Survey of Family Growth. After recovering preferences for gender variety, we simulate the introduction of this technology. While this technology can reduce fertility by allowing parents efficiently reach their preferred gender mix, it could also increase fertility. This is because without this technology, many parents may opt not to have another baby given the uncertainty about its gender. Preliminary results suggest that these two effects operate simultaneously, but on net, gender selection technology ends up increasing the total fertility rate by about ten percent in the steady state.

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## 1 Introduction and Motivation

In the United States, many parents "keep trying" until they have a child of a specific sex. It is likely that underlying this quest are strong parental preferences for gender variety in their offspring. Many women who would ideally have had only one boy and one girl may end up with three or even four children of the same gender before eventually giving up. Even if the mother reports loving them all equally, it is clear that from an economic perspective there is a friction, namely the uncertainty about gender at the time of conception, that may create significant welfare losses in the population at large. A less overt, more subtle phenomenon occurs when a mother of one, would like to enjoy this very same gender variety but decides not to go for a second child because of the fear that it might end up being of the same gender as the first one. Here again, some welfare loss is associated with the uncertainty friction.

In recent years, however, highly accurate methods of gender selection have been developed. While their use is of course subject to heated debate from a bioethical standpoint, a standard economic perspective sees gender selection as a welfare improving technology that eliminates this "gender uncertainty" friction and allows parents to more precisely target their desired gender mix.

In this paper we do not weigh in the debate on the morality of gender selection technology but rather ask a simple positive question: what would be the demographic consequences of widely available, easily affordable gender selection technology? This a simple, yet difficult to answer question. The main problem comes from the lack of variation across time and/or space in meaningful exposure to the technology. Therefore a standard empirical strategy leveraging the behavioral differences among those who are exposed and those who are not, is not available. To tackle the question we develop a dynamic model of sequential fertility decisions that features explicit preferences for gender variety. We leverage the quasi-experimental variation inherent in the plausibly random determination of gender at the time of conception to identify the key structural parameter characterizing preferences for gender variety. We then estimate the model using data from the National Survey of Family Growth and use the estimated model to conduct a simple counterfactual involving the introduction of a low cost and morally acceptable gender selection technology. While preliminary, our findings are somewhat surprising: gender selection technology could lead to an increase of up to 10 percent in the total fertility rate.

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 reduce form evidence suggestive of strong preferences for gender 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 a counterfactual experiment to assess the demographic consequences of gender selection technology.

2 Technology and Policy Background

It is worth first getting some background on the technology of gender selection. Methods to select gender can be distinguished by whether they select before or after conception. The latter is usually more ethically objectionable. Let’s begin with sex-selection before conception. Over the centuries folklore has contained various prescriptions for conceiving a child of a particular sex. However none of these folk methods have proven reliable. On a more scientific level, several methods have been examined for conceiving a child of a particular sex. They include the timing of intercourse during the woman’s menstrual cycle\(^1\), the time of artificial insemination\(^2\), the provision of acidic (or alkaline) environments for sperm\(^3\), the degree of penetration\(^4\), a woman’s diet\(^5\). More invasive procedures involve injecting the woman with antibodies against androgenic (i.e., male-determining, Y-bearing) sperm or

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\(^1\)One theory is that the timing of intercourse and conception can alter the odds of producing a male or female child. Because androgenic spermatozoa tend to be more numerous, and because they have been thought to be shorter-lived and faster-moving than gynogenic spermatozoa, it has been hypothesized that intercourse close to the time of ovulation is more apt to produce male conception, while intercourse several days prior to ovulation is more apt to produce females. In a popular book on sex selection Rorvik and Shettles (1970) recommended that couples wanting boys should have intercourse close to the time of ovulation, while those wanting girls should have intercourse several days prior to that time. However, Whelan (1977) argued that this schedule actually lowers the probability of getting a child of the desired sex.

\(^2\)Some researchers have claimed that the appropriate schedules are reversed in the case of artificial insemination. Guerrero (1970) has reported that natural inseminations early and late in the fertile period produce more males than those nearer to the time of ovulation, while the opposite effect occurs with conceptions resulting from artificial insemination. However, the evidence is so inconsistent that no method of sex selection involving timing appears particularly promising. For a summary of research on the influence of the timing of conception, see James (1983)

\(^3\)Acidic environments are more favorable to gynosperm, while alkaline environments favor androsperm. Rorvik and Shettles (1970) recommend the use of acid douches to increase the odds of conceiving a girl, and alkaline douches to increase the odds of a boy. However the reliability of these methods has not been established.

\(^4\)Couples wishing to conceive a boy have been advised to use deep penetration, since the secretions of the cervix are thought to be less acidic than those of the vagina. However, these methods have not been proven to be reliable. See Warren (1985).

\(^5\)Fetal sex can be influenced by the mother’s diet in the weeks prior to conception. Stolkowski and Choukroun (1981) advise that a woman who wants to conceive a boy should eat foods high in sodium and potassium; for a girl, she should eat foods high in calcium and magnesium. The assumption is that a woman’s internal mineral balance may affect the consistency of her cervical mucus, or some other environmental condition within her reproductive tract, making it more hospitable to sperm of one or the other sort. Several other researchers have recommended particular diets for the production of boys or girls. So far, however, there has been no experimental confirmation of such claims, and most fertility researchers regard the odds of selecting sex through diet as close to nil. See Warren(1985), Langendoen and Proctor (1982) and Lorrain and Gagnon (1975).
gynogenic (i.e., female-determining, X-bearing) sperm.\textsuperscript{6} While none of these more scientific methods have proven reliable, the fact that the research community has explored them in some detail indicates the level of interest on this topic.

While there has also been speculation about the eventual development of a sex-selection pill or a sex-selective diaphragm\textsuperscript{7}, the only currently proven methods of sex-selection before conception involve sperm separation techniques followed by artificial intrauterine insemination\textsuperscript{8} with a sperm sample carrying mostly the preferred sex chromosome or in-vitro fertilization (PGD) followed by prenatal genetic diagnosis (PGD) and the transfer of only male or female embryos back into the uterus. These methods increase the probability of conceiving a child of a particular sex\textsuperscript{9}. Sperm contain, among 22 chromosomes, one X or one Y chromosome, which will determine at fertilization the sex of the offspring. The most recent method of sperm separation is called MicroSort and uses a clever technology: X chromosomes have about 2.8\% more DNA than Y chromosomes. By staining sperm with a fluorescent dye that latches onto DNA and measuring the glow of the sperm cells under laser light, one can gauge how much genetic material each one carries. Once the sperm has been distinguished in this way, an automated sorting machine separates the Xs from the Ys.\textsuperscript{10} The woman can then be artificially inseminated with the sorted sample carrying sperm mostly bearing the desired chromosome. It should be noted that sperm separation followed by artificial insemination is much less invasive and substantially less expensive than IVF+PGD and has therefore much more potential for widespread adoption by the average household.

There are also several ways to select gender after conception. These procedures involve determining the sex of the child that has already been conceived through some form of prenatal diagnosis, such as amniocentesis or ultrasound, and then aborting a child of an unwanted sex. Of course this method is on morally shakier grounds, especially when compared to methods that sex-select before conception. It is also difficult to implement as ultrasounds for gender determination are usually performed at the 20th week and at that time is usually too late to find a provider willing to conduct an abortion.\textsuperscript{11}

While sex-selection is also explicitly banned in several developed countries the situation in the U.S. is different. The regulatory jurisdiction within which most of these methods

\textsuperscript{6}See Bayles (1984) and Hull (1990).
\textsuperscript{7}See Warren (1985)
\textsuperscript{8}While more expensive and invasive, in vitro fertilization with the concentrated sperm sample can also be used.
\textsuperscript{9}Ericsson (1982) reported a success rate of about 75\% percent for the conception of boys by his technique.
\textsuperscript{10}MicroSort technology offers couples an 85\% chance of conceiving a girl and a 65\% chance of conceiving a boy. See Golden (1998).
\textsuperscript{11}Note however that in 2009 a home urine test for gender determination, IntelliGender was introduced in the market. This test allegedly provides accurate gender determination as early as 10 weeks into the pregnancy. Is currently available in pharmacies. Its cost is only $30.
belong is not very well defined. The framework used to be one of discouragement as opposed to outright prohibition. For example, on the issue of sex selection before conception, the Council on Ethical and Judicial Affairs of the American Medical Association has taken the position that "sex selection of sperm for the purposes of avoiding a sex-linked inheritable disease is appropriate." At the same time, the Council maintains that "physicians should not participate in sex selection for reasons of gender preference" but "should encourage a prospective parent or parents to consider the value of both sexes."\textsuperscript{12}

However, in recent years the development of MicroSort’s inexpensive, minimally invasive and highly accurate technology raised the policy stakes on the issue. At the time of this writing, however, the Genetics and IVF Institute, sponsor of MicroSort clinical trials, has not yet pursued approval from the FDA to market this technology within the U.S. for family balancing purposes\textsuperscript{13}.

3 Data and Quasi-Experimental Evidence

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, non-institutionalized population of the United States. In particular, for each woman, we have the year of birth and gender of each of her children.

We use the birth histories of female respondents by the time of interview to recover the fertility choices each of these women made at each age during their reproductive years (starting at age 15 and leading up to the age at the time of the NSFG interview). The age at 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 chose to have a child at age $a$.\textsuperscript{14} In addition to fertility histories, the NSFG also provides information on the completed years of education level that these women have females achieved by the time of interview. We use completed years of education by interview to classify NSFG women into to low education and high education groups. The high education group includes women with at least some college. The low education group 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

\textsuperscript{12}See American Medical Association (1993)

\textsuperscript{13}The procedure is still available for couples attempting to prevent a sex-linked genetic disease.

\textsuperscript{14}For simplicity, we therefore organize the panel at the annual level, the unit of time to be used in the model below, as opposed to 9 months intervals, which is of course more accurate.
sample to those who were 25 years of age or older at time of interview.

Our final estimation sample consists of 25,943 female respondents aged between 25 and 44 from several NSFG waves spanning 1982-2008. We excluded respondents who had more than 4 live births by the time of interview. We also drop women who had a first live birth before the age of 16 or have ever had multiple live births in a single year.

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 low and high education groups. Of course, the pattern 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, and as documented elsewhere, women with more education tend to have less children.

Table 2 shows the distribution of gender specific completed fertility at the time of interview. As can be seen in the table, completed fertility follows a fairly symmetric pattern,

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16 Among women who are at least 40 years old at the time of interview, less than 6% have more than four live births.
Table 2

Gender Specific Completed Fertility by Time of Interview

<table>
<thead>
<tr>
<th>Number of girls</th>
<th>nb 0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>18%</td>
<td>9%</td>
<td>8%</td>
<td>2%</td>
<td>1%</td>
<td>37%</td>
</tr>
<tr>
<td>1</td>
<td>10%</td>
<td>18%</td>
<td>7%</td>
<td>2%</td>
<td>36%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>9%</td>
<td>8%</td>
<td>3%</td>
<td>20%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>4%</td>
<td>2%</td>
<td>6%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1%</td>
</tr>
</tbody>
</table>

Total 42% 36% 18% 4% 1% 100%

Note: Sample restricted to women 40 and older at time of interview. Pooled samples from NSFG waves 1982-2008

an indication that gender bias is less apparent in the U.S. than in countries like India and China.

Another important difference between high and low education women is related to the timing of births. As can be seen in Figure 1, the distribution of age at first birth peaks at age 19 years for women with low education while it peaks much later for highly educated women. Their median age at first birth is 26.

While there is no overt evidence of gender-biased preferences in the United States, Angrist and Evans (1998) document strong preferences for gender variety among American households. Consider women at parity $n = 2$ and define indicators SubsequentBirth$_i$ and Same-Sex$_i$ as follows

\[
\text{SubsequentBirth}_i = \begin{cases} 
1 & \text{if woman } i \text{ is observed to have at least one more birth before interview} \\
0 & \text{otherwise}
\end{cases} \quad (1)
\]

\[
\text{Same-Sex}_i = \begin{cases} 
1 & \text{if the (two) children born so far to woman } i \text{ are of the same sex} \\
0 & \text{otherwise}
\end{cases} \quad (2)
\]
A simple linear probability model for Subsequent Fertility (the observation of a third birth due to the same woman at some point before interview) is given by

$$\text{SubsequentBirth}_i = \alpha_0 + \alpha_1 \text{Same-Sex}_i + \varepsilon_i$$  \hspace{1cm} (3)

Under some assumptions, Same-Sex$_i$ is as good as randomly assigned. Angrist and Evans present suggestive evidence of strong preferences for gender variety by showing that $\alpha_1$ is positive, significant and sizable in magnitude. In words, American households are much more likely to be observed to have a third birth when the first two are of the same sex. Here we replicate Angrist and Evans’ findings with our NSFG data. Table 3 presents the results. Column 1 presents the basic estimates while column 3 controls for age at second birth and age at interview effects. In both cases we find strong evidence of preferences for gender variety.

It is also possible to use the type of variation emphasized in Angrist and Evans’ specifi-
Table 3
Angrist and Evans (1998) in the NSFG

<table>
<thead>
<tr>
<th></th>
<th>Woman Had a 3rd Birth</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Two Children of Same Gender</td>
<td>0.0474*** 0.0472***</td>
</tr>
<tr>
<td></td>
<td>(0.00836) (0.00769)</td>
</tr>
<tr>
<td>First Two Children are Males</td>
<td>0.0585*** 0.0534***</td>
</tr>
<tr>
<td></td>
<td>(0.00999) (0.00922)</td>
</tr>
<tr>
<td>First Two Children are Females</td>
<td>0.0342*** 0.0398***</td>
</tr>
<tr>
<td></td>
<td>(0.0105) (0.00965)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.388*** 0.388*** 0.513*** 0.513***</td>
</tr>
<tr>
<td></td>
<td>(0.00588) (0.00588) (0.0475) (0.0475)</td>
</tr>
<tr>
<td>Age at 2nd Birth Effects</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Age at Interview Effects</td>
<td>✓ ✓</td>
</tr>
</tbody>
</table>

Test Ho: all males= all females
F(1,13831) 4.16 1.54
p-value 0.04 0.22
Observations 13,834 13,834 13,827 13,827
Mean of Dep. variable 0.412 0.412 0.412 0.412

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Subsample of women who were at least 25 years old at the time of interview and that had at least two children by the time of interview. Polled waves from NSFG 1982-2008.
cation to test for gender bias. Define the following indicators

\[
\text{All Boys}_i = \begin{cases} 
1 & \text{if all children born (so far) to woman } i \text{ are boys} \\
0 & \text{otherwise}
\end{cases}
\] (4)

\[
\text{All Girls}_i = \begin{cases} 
1 & \text{if all children born (so far) to woman } i \text{ are girls} \\
0 & \text{otherwise}
\end{cases}
\] (5)

Now consider the modified linear probability model given by

\[
\text{Subsequent Birth}_i = \alpha_0 + \alpha_b \text{All Boys}_i + \alpha_g \text{All Girls}_i + \varepsilon_i
\] (6)

Note that the relative magnitudes of \(\alpha_b\) and \(\alpha_g\) can be used to test for gender bias. In particular, if \(\alpha_b \neq \alpha_g\), women prefer the gender with lowest \(\alpha\). Columns 2 and 4 of Table 3 present the results of the gender bias test. The coefficient \(\alpha_b\) on All Boys\(_i\) is much larger than \(\alpha_g\), implying potential gender preferences in favor of girls (women are more likely to go for a third birth if they have had only boys). The magnitude of the difference is relatively large and indeed in Column 2 we reject that the 2 coefficients are equal. However, we fail to reject this null of "no gender bias" in Column 4, once we control for age at second birth and age at interview.

While these results are interesting and useful in their own right, they don’t allow us to predict the consequences of gender selection technology. Whenever a woman with two children of the same gender decides not to go for another child, we can’t tell whether she would had gone for it, had the technology to secure its gender 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 gender, we cannot distinguish whether the decision not to go for a third child stems primarily from lack of strong preferences for variety or from the potential reduction in utility associated with having three children of the same gender, if the third child turns out to have the same gender as the first two.

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 gender 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 sequential, 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.\footnote{17}{Early papers by Becker (1960), Willis (1973) and Becker and Lewis (1973) pioneered the study completed fertility in a static, single shot context in which the entire life-cycle constitutes a single decision period. Building on this early work Heckman and Willis (1976) were the first to think about issues of sequentiality, dynamics and uncertainty.}

In this section we write a formal estimable model that allows for preferences for gender variety. In particular, we incorporate explicitly a specification of preferences for a diverse gender mix as in Rosenzweig and Wolpin (2000).\footnote{18}{We do not distinguish whether a specific gender composition affects enter directly throught children services in the flow utility or through its potential impact on household consumption opportunities through the budget constraint. In that sense, our flow utility is an indirect utility function. Rosenzweig and Wolpin (2000) highlight the fact that lack of gender variety may generate hand me down cost savings as children of the same gender 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.}

This is the crucial added feature of our model, which was not present in previously estimated dynamic structural models of fertility.\footnote{19}{Ahn (1995) was the first to allow the value of children to vary by gender in an estimated dynamic programming model of fertility. However, while allowing for gender differences in the value of children, his model does not allow for explicit parental preferences for gender variety.}

At each and every age within their reproductive years, women choose to give birth to a child or not.\footnote{20}{We follow Wolpin (1984), Ahn (1995) and Gayle and Miller (2012) in assuming that fertility can be perfectly controlled. See Rosenzweig and Schultz (1985), Montgomery (1988), Hotz and Miller (1988,1993) and Carro and Mira (2006) for dynamic models of fertility with stochastic reproduction and contraception. See also David and Mroz (1989) who describe how conception hazards evolve with successive demographic events. Moreover, we abstract away from infertility issues. See Carro and Mira (2006) for a model with unobserved heterogeneity in fecundity. We also assume that women are sexually active from age 15 onwards. See Arcidiaceno, Khwaja and Ouyang (2012) for a model of sexual activity onset.}

We denote $d_{ja}$ to be the indicator of whether choice $j$ was taken. We use $j = 1$ when they choose not have a birth and $j = 2$ when they choose to have a birth. For tractability, we allow women to have up to four children and they must choose $j = 1$ after that.

An explicit joint modeling of female fertility and labor supply would be needed if our goal here were 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 gender selection technology that could allow parents to satisfy their specific preferences for gender composition. As a result, in what follows we abstract 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. While abstracting from an explicit economic modeling of timing and spacing, we retain the sequential, dynamic framework to properly handle gender uncertainty. Parents in our model have reproductive policy functions that can potentially depend on (are contingent upon) the realized gender of each child. In other words, some parents may need to wait and see what the gender mix of their first two children is, before deciding on whether to seek a third pregnancy. This requires a dynamic model.

Let the state vector at age $a$ be $x_a = [a, n^b_a, n^g_a, e]$ where $a$ is age in years, $n^b_a$ is the number of boys by age $a$, $n^g_a$ is the number of girls by age $a$ and $e$ is an indicator for low ($e = 1$) or high ($e = 2$) education.

The transition probability for the state variables that keep track of the stock of children is denoted by $f_{ja}(x_{a+1}|x_a)$ and it is trivial.

$$\Pr (n^b_{a+1} = n^b_a + 1 \cap n^g_{a+1} = n^g_a | d_{2a} = 1) = 0.5$$

$$\Pr (n^b_{a+1} = n^b_a \cap n^g_{a+1} = n^g_a + 1 | d_{2a} = 1) = 0.5$$

$$\Pr (n^b_{a+1} = n^b_a \cap n^g_{a+1} = n^g_a | d_{2a} = 0) = 1$$

Period utility is given by

$$u_{ja}(x_a) + \varepsilon_{ja}$$

where $\varepsilon_{ja}$ is an i.i.d. (across individuals, ages and alternatives) preference shock to the utility of alternative $j$. We assume that $\varepsilon_{ja}$ has Extreme Value distribution. The systematic component $u_{ja}(x_a)$ depends on number and gender composition in the current stock of children

$$u_{ja}(x_a) = \alpha_1 n_a + \alpha_2 n^2_a + \alpha_3 I \{n^g_a = 0 \cup n^b_a = 0\} + \varphi_{ja}^e$$

where

$$\varphi_{2a}^1 = \varphi_{20}^1 + \varphi_{20}^1 (a - 15) + \varphi_{20}^1 (a - 15)^2$$

$$\varphi_{2a}^2 = \varphi_{20}^2 + \varphi_{20}^2 (a - 15) + \varphi_{20}^2 (a - 15)^2$$

and we normalize $\varphi_{1a}^e = 0$ for all $(a, e)$

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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 (2012). 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.

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).
Note that \( \alpha_3 \) is a critical parameter in our model as it captures the disutility flow from lack of gender variety. Moreover, we could allow for potential gender bias by specifying the total effective number of children entering the utility function as

\[
n_a = \rho n_a^b + n_a^g
\]  

(10)

where \( \rho \) is a structural parameter that captures the degree of gender bias. If \( \rho = 1 \) there is no gender bias. If \( 0 < \rho < 1 \) there is a preference for girls and if \( \rho > 1 \) there is a preference for boys.\(^{23}\) From now on we collect all the parameters in a vector \( \theta \).

Women maximize expected lifetime utility by choosing the optimal quantity, timing and spacing of births.\(^{24}\)

\[
\max \left\{ \frac{\sum_{a=15}^{\tilde{A}} \sum_{j=1}^{2} \beta^{a-15} d_{ja} [u_{ja}(x_a; \theta) + \varepsilon_{ja}]}{\sum_{a=15}^{\tilde{A}} \sum_{j=1}^{2} \beta^{a-15} d_{ja} [u_{ja}(x_a; \theta) + \varepsilon_{ja}]} \right\}
\]  

(11)

where \( \tilde{A} \) is the last period of life, \( \tilde{\tilde{A}} \) is the last year in which the woman can have a child and \( \beta \) is the discount factor.\(^{25}\) The economic trade-off in the dynamic optimization problem is straightforward. Since children provide services in the flow utility, women have an incentive to have them as soon as possible to enjoy them the most. However, they also must take into account the fact that for reasons not structurally modelled here, it might not be optimal to start so early. This is captured mostly in a reduced form by our quadratic age specification for \( \varphi_{ja} \).\(^{26}\) Also, over an above these considerations, women must optimally wait for an age in which it is specially appropriate to have a birth (i.e., an age at which they receive a large \( \varepsilon_2 \)). Yet, they are fully aware that their reproductive years are limited and so their optimal policy functions take into account approaching the menopause age, assumed to occur at age \( \tilde{A} + 1 \), with probability one. Also, the model has the potential to generate the type of findings in the work of Angrist and Evans and documented above for our sample. In particular, \( \alpha_3 < 0 \) implies that women who, by age \( a \) have either \( (n_a^b = 2, n_{a+1}^g = 0) \) or


\(^{24}\)As noted above, we restrict the number of possible births to four. After reaching four, women must choose \( j = 1 \) but they continue to receive preference shocks associated with this alternative.

\(^{25}\)Note that \( \varepsilon_a = (0, 0) \) and \( d_{ja} = 1 \) for \( a > \tilde{A} \). We use \( \tilde{A} = 43 \) and \( \bar{A} = 75 \).

\(^{26}\)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).
(n^n = 0, n^{g+1} = 2) will have a larger incentive to have another (a third) birth than those who have (n^n = 1, n^{g+1} = 1). Moreover, \( \rho < 1 \) implies gender preferences for girls and therefore gives those with \( (n^n = 2, n^{g+1} = 0) \) a larger incentive than those with \( (n^n = 0, n^{g+1} = 2) \) to go for a third birth.

Let \( d^n (x, \varepsilon) = (d^n_1 (x, \varepsilon), d^n_2 (x, \varepsilon)) \) be the optimal decision rule at age \( a \) and denote by \( p_{ja} (x) \) the probability of choosing action \( j \) at age \( a \) conditional on state \( x \)

\[
p_{ja} (x) = \int d^n_{ja} (x, \varepsilon) g (\varepsilon) \, d\varepsilon
\]

\( V_a (z_a) \) is the ex-ante value function at age \( a \) before the realization of \( \varepsilon_a \)

\[
V_a (x) = E \left[ \sum_{\tau = a}^{\hat{A}} \sum_{j = 1}^{2} \beta^{\tau-a} d_{ja}^{\tau} \left[ u_{ja} (x_{\tau}) + \varepsilon_{ja} \right] \right]
\]

\[
V_a (x) = E \left[ \sum_{j = 1}^{2} \int d_{ja}^{\tau} (x_a; \varepsilon_a) \times \left[ u_{ja} (x_a) + \varepsilon_{ja} + \beta \sum_{x_{a+1} \in X_{a+1}} V_{a+1} (x_{a+1}) f_{ja} (x_{a+1} | x_a) \right] g (\varepsilon_a) \, d\varepsilon_a \right]
\]

and \( v_{ja} \) is the choice-specific value function (net of preference shock \( \varepsilon_{ja} \))

\[
v_{ja} = u_{ja} (x_a) + \beta \sum_{x_{a+1} \in X_{a+1}} V_{a+1} (x_{a+1}) f_{ja} (x_{a+1} | x_a)
\]

5 Structural Estimation

To estimate the model we solve the dynamic programming problem through backwards recursion for given structural parameters and embed this solution in a maximum likelihood estimation routine. The parameters to be estimated are

\[
\theta = (\alpha_1, \alpha_2, \alpha_3, \varphi_{20}, \varphi_{21}, \varphi_{22}, \varphi_{20}, \varphi_{21}, \varphi_{22}, \rho)
\]

The likelihood function is given by

\[
L (\theta; \text{Data}) = \prod_{i=1}^{N} L_i (\theta, x_i, d_i)
\]

So the log likelihood is
\[
\log L (\theta; \text{Data}) = \log \left( \prod_{i=1}^{N} L_i (\theta, x_i, d_i) \right) \\
= \sum_{i=1}^{N} \log L_i (\theta, x_i, d_i)
\]

The key component of the likelihood function is the individual likelihood contribution, \( L_i (\theta, x_i, d_i) \). Let \( A_{i}^{\text{NSFG}} \) be the age at the time of NSFG interview for woman \( i \). The transition data can be factored out so the likelihood contribution for woman \( i \), with given history of states and choices \( \{d_{ia}\}_{a=15}^{A_{i}^{\text{NSFG}}-1}, \{x_{ia}\}_{a=15}^{A_{i}^{\text{NSFG}}} \), is just the probability of observing the sequence of fertility choices that she made. Since the shocks to preferences \( \varepsilon \) are i.i.d. over time, the probability of the sequence of choices is just the productoria of the choice probabilities for each age conditional on the state at that age.

\[
L_i (\theta, x_i, d_i, s_i = s) = \prod_{a=15}^{A_{i}^{\text{NSFG}}} \Pr (d_{ia} | x_{ia}, \theta) \\
= \prod_{a=15}^{A_{i}^{\text{NSFG}}} \left[ \prod_{d=1}^{2} \Pr (d_{ia} = d | x_{ia}, \theta)^I_{d_{ia}=d} \right]
\]

Now, to compute \( \Pr (d_{ia} = d | x_{ia}) \) we use the solution to the dynamic programming problem. Recall

\[
v_{da} (x_{ia}, \theta) = u_d (x_{ia}, \theta) + \beta E \max_{\bar{J} (x_{a+1})} \left\{ v_{j,a+1} (x_{a+1}, \theta) + \varepsilon_{j,a+1} \right\} | x_{ia}, d_a = d \\
= u_d (x_{ia}, \theta) + \beta \sum_{x_{i,a+1}} E_{\varepsilon} \max_{\bar{J} (x_{a+1})} \left\{ v_{j,a+1} (x_{a+1}, \theta) + \varepsilon_{j,a+1} \right\} | x_{a+1} \\
= f_d (x_{a+1})
\]

where \( \bar{J} (x) \) is the set of choices available to a woman when she is in state \( x \),\(^{27}\) and where given our distributional assumptions on \( \varepsilon \), \( E_{\varepsilon} \left[ \max_{\bar{J} (x_{a+1})} \{ v_{j,a+1} (x_{a+1}, \theta) + \varepsilon_{j,a+1} \} | x_{a+1} \right] \) has the closed form solution noted by Rust (1987).

\(^{27}\)Note that we only allow up to four births in the model, so the choice set excludes the birth alternative once the woman has had four children.
Table 4

Maximum Likelihood Estimates

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<tr>
<td>phi22(high edu)</td>
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<td>0.0003</td>
</tr>
</tbody>
</table>

\[ E_\varepsilon \left[ \max_{j \in J(x_{a+1})} \{v_{ja+1}(x_{a+1}, \theta) + \varepsilon_{ja+1} \} | x_{a+1} \right] = \gamma + \ln \left( \sum_{j \in J(x_{a+1})} \exp (v_{ja+1}(x_{a+1}, \theta)) \right) \tag{24} \]

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

\[ \Pr (d_{ia} = d | x_{ia}, \theta) = \frac{\Pr (v_{da}(x_{ia}, \theta) + \varepsilon_{da} > v_{ja}(x_{ia}, \theta) + \varepsilon_{ja} \ \forall j \neq d)}{\sum_{j \in J(x_{ia})} \exp (v_{ja}(x_{ia}, \theta))} \tag{25} \]

Note that another advantage of Rust(1987) framework is that the choice probability also has closed form.

Table 4 presents the maximum likelihood estimates for the structural parameters \( \alpha_3 \) is negative and significant, implying non-negligible disutility for those women who have not yet achieved gender variety. Given our results in Section 2 we estimated the model ruling out gender bias and therefore setting \( \rho = 1 \). The parameter estimates in Table 4 as well as model fit figures and counterfactual results below are based on this specification. We also normalize \( \alpha_1 = 1 \) as it is not separately identified from \( \varphi_{20} \).

\[ \text{Identification of } \rho \text{ is not trivial as the unconditional observation of a woman’s decision to have a birth conveys no identifying information about } \rho \text{ because the gender is uncertain. Of course, as discussed in Section 2, a significantly higher propensity to go for a third birth among women who had two boys, relative to women who had two girls would provide evidence of gender bias towards girls.} \]
5.1 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 in the NSFG data. The model matches very well completed fertility by time of interview

\[ \frac{1}{N} \sum_{i=1}^{N} \left( n_{A_{i}^{bs}} + n_{A_{i}^{gs}} \right) \].

Moreover, as can be seen in Figures 2 and 3, the model does a great job at matching gender specific completed fertility by time of interview for both education groups.

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 women who have had at least one birth by the time of interview. Figures 4 and 5 present the results.

6 Counterfactual Experiment: Gender Selection Technology

A widely available, easily affordable, morally sound gender selection technology would presumably allow more precisely target the desired gender mix. In particular fertility could be reduced if parents need fewer attempts to achieve gender variety in their offspring. On the other hand, this very same technology could increase fertility by reducing the gender uncertainty about the child that is being 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 the fertility rate would be positive or negative.

To answer the question we the re-solve dynamic optimization problem using the estimated
parameters $\hat{\theta}$, but now allowing for an expanded choice set that makes use of gender selection
technology

$$d_a = \begin{cases} 
1 & \text{if no birth} \\
2b & \text{if have a boy} \\
2g & \text{if have a girl}
\end{cases} \quad (26)$$

where the alternative specific value function associated with having a birth $j = 2$ is now
given by

$$v_2(x_a) = \max \left[ v_2(x_a|j = 2b) ; v_2(x_a|j = 2g) \right] \quad (27)$$

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

$$v_{2a}(x_{ia}, \theta|j = 2b) = u_2(x_{ia}, \theta) + \beta E_{\varepsilon} \left[ \max_{j \in S^{(x_{a+1})}} \left\{ v_{j,a+1}(n_a^g, n_a^b + 1, \theta) + \varepsilon_{j,a+1} \right\} | x_{a+1} \right] \quad (28)$$

$$v_{2a}(x_{ia}, \theta|j = 2g) = u_2(x_{ia}, \theta) + \beta E_{\varepsilon} \left[ \max_{j \in S^{(x_{a+1})}} \left\{ v_{j,a+1}(n_a^g + 1, n_a^b, \theta) + \varepsilon_{j,a+1} \right\} | x_{a+1} \right] \quad (29)$$
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 15 to 44 for all simulated women. We do this both in the baseline and counterfactual simulations. 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 "birth" and the "no birth" option and do not introduce preference shocks for gender specific births. Again, given that the model is estimated on data assumed to have been generated under a regime in which gender selection opportunities are not available, the proper structural interpretation of $\varepsilon_{2a}$ is that of an unobserved taste shifter that makes having a birth at age $a$, whatever its gender, a particularly good idea. Moreover, introducing a third shock would distort the value functions as the maximum over three realizations of $\varepsilon$ is of course larger than the maximum over two and this extra source of utility would be over and above the one generated by the fact that $v_2(x_a) = \max [v_2(x_a|j = 2b) ; v_2(x_a|j = 2g)]$ instead of $v_2(x_a) = \frac{1}{2}v_2(x_a|j = 2b) + \frac{1}{2}v_2(x_a|j = 2g)$.

To begin, we first explore the impact on overall completed fertility for a given cohort. Table 5 presents the results of a steady state comparison in the sense that, in both cases, baseline and counterfactual, the cohort is exposed to the alternative regimes from age 15 onwards.

As can be seen in the table, there is a substantial decline of approximately 30 percent (6 percentage points) in childlessness. The fraction of women with only one child also declines from 21% to 13% whereas almost half of them (46%) end up with two children in the counterfactual. The changes are much smaller at higher parities. By looking at Table 5 we can already see that the net impact of this technology on overall fertility is actually positive.

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<tr>
<td>nb+ng=4</td>
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<td>12%</td>
</tr>
</tbody>
</table>

Table 5
Steady State Impact of Gender Selection Technology on Completed Fertility

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 15 to 44 for all simulated women. We do this both in the baseline and counterfactual simulations. 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 "birth" and the "no birth" option and do not introduce preference shocks for gender specific births. Again, given that the model is estimated on data assumed to have been generated under a regime in which gender selection opportunities are not available, the proper structural interpretation of $\varepsilon_{2a}$ is that of an unobserved taste shifter that makes having a birth at age $a$, whatever its gender, a particularly good idea. Moreover, introducing a third shock would distort the value functions as the maximum over three realizations of $\varepsilon$ is of course larger than the maximum over two and this extra source of utility would be over and above the one generated by the fact that $v_2(x_a) = \max [v_2(x_a|j = 2b) ; v_2(x_a|j = 2g)]$ instead of $v_2(x_a) = \frac{1}{2}v_2(x_a|j = 2b) + \frac{1}{2}v_2(x_a|j = 2g)$.

To begin, we first explore the impact on overall completed fertility for a given cohort. Table 5 presents the results of a steady state comparison in the sense that, in both cases, baseline and counterfactual, the cohort is exposed to the alternative regimes from age 15 onwards.

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Table 6 presents a more detailed picture of the impact of gender selection technology by looking at what happens to gender-specific completed fertility.

The first obvious pattern that emerges from the table in column 4 is that since $\alpha_3$ is negative, multi-child gender-unbalanced stocks $(n^b, n^g) = (2, 0), (0, 2), (3, 0), (0, 3), (4, 0)$ and $(0, 4)$ all have zero incidence in the counterfactual simulation as there is a "flight to gender variety". This is partly a result of a) the fact that preference shocks to the birth alternative are not gender specific, b) the fact that we are not allowing for unobserved heterogeneity in $\alpha_3$ and c) the fact that we are not allowing for any non-pecuniary, nor pecuniary costs of using the technology. In that sense, the counterfactual is only relevant in a world in which moral and monetary obstacles for widespread use have been completely removed.\(^{29}\) The simulations then provide an upper bound for the overall fertility impact one might expect in the short run.\(^{30}\) As expected, parents with one boy and one girl $(n^b, n^g) = (1, 1)$ become the overwhelming majority: the share of women with this particular gender composition in

\(^{29}\)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 to identify those who would not use the technology on moral or bioethical grounds.

\(^{30}\)Another reason this is an upper bound is that the model is partial equilibrium in nature and doesn’t take into account second order feedback effects from labor and marriage markets. These feedbacks could arguably mitigate the direct impact of this technology on fertility.
their completed fertility soars from 18 to 46%. Women with (1, 0) or (0, 1) go from 11% to 6% and the fraction with (2, 1) or (1, 2) increases slightly.

An more informative way to explore at the impact of this technology is to tabulate what is the distribution of \((n^b, n^g)\) under the counterfactual regime with gender selection, for each \((n^b, n^g)\) at baseline. Table 7 presents the results.

The decomposition shows several interesting results. For example, almost half (47%) of those with \(n^g + n^b = 1\) at baseline end up with 2 children in the counterfactual whereas only 24% of those with \(n^g + n^b = 3\) at baseline do so. A vast majority (87%) of those with \(n^g + n^b = 2\) remain with two children. This last results masks important changes, though. From the previous tables we know that nobody ends at \((0, 2)\) or \((2, 0)\) in the counterfactual. Table 8 provides even deeper insight into the wide ranging changes that would be brought by the availability gender selection.

Again, columns involving no variety are full of zeros. 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 \((2, 2)\)) "exports" some women to \((n^b, n^g) = (1, 1)\) in the counterfactual. In addition to those who had \((1, 1)\) at baseline, the major contributing configurations are \((0, 2)\) and \((2, 0)\), both with 86% of their baseline women having \((1, 1)\) once gender selection technology is introduced. Also, more than 40% of those with \((0, 3)\) or \((3, 0)\) at baseline end up with \((1, 1)\). These are the women who took their chances to reach variety and failed. The realistic timing of the model set up as well as its stochastic structure generate 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 certainty about gender can generate changes in the optimal timing of births. These changes in turn can open opportunities for additional births. Indeed, up to 12% of those with \((1, 1)\) at baseline end up with \((1, 2)\) or \((2, 1)\) in the counterfactual.
While we are not able to compute explicit welfare gains. This table portrays a potentially large increase in welfare. Of course, we know welfare will increase as women have an additional option, but what’s striking is how widespread are the effects. Almost every woman is affected: some of them increase their fertility, some of them decrease it and some of them stay at the same parity yet adjust the gender mix in their offspring. Each and everyone of these changes involves a potentially large welfare gain.

Finally, we look at the implications for the total fertility rate. In a stationary world, this is akin to look at the cross-sectional fertility rate of several overlapping cohorts at a single point in time. Table 9 presents the results.

The overall impact of gender selection technology is to increase the total fertility rate by approximately 10%, from 1.8 to 2.0. Notably the TFR for highly educated women also increases from 1.56 to 1.78. This is important as many policies designed to promote fertility usually have more success at the low end of the socioeconomic spectrum.

### 7 Conclusions and Future Work

Fertility preferences in the U.S. are for the most characterized by a strong desire to achieve gender variety. Emerging technologies might soon put gender selection opportunities within the reach of average American households. Beyond bioethical considerations, it is important to gauge what the demographic impact of these technologies could be. In this paper,
Table 9

Impact of Gender Selection Technology on Fertility Rates

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TFR 1.81 2.08 1.56 2.00 2.25 1.78
we formulate a dynamic programming model of sequential fertility decisions that explicitly allows for gender variety. We estimate the model via maximum likelihood using microdata from the National Survey of Family Growth. Despite model parsimony, the model replicates key features of the NSFG such as the education specific patterns of completed fertility and distributions of age at first birth. Our preliminary results suggest that a widely available and easily affordable gender selection technology would increase the total fertility rate by about 10%. This net effect involves several changes for different women with some increasing, some decreasing their completed fertility and some just adjusting their gender mix. In the simulations, several households are induced to change their fertility behavior upon the introduction of this technology, implying large potential gains in welfare.

In future work we plan to extend the model by allowing for persistent forms of unobserved heterogeneity and by incorporating more details of the birth history into the state space. Work by Hotz and Miller (1988) and Gayle and Miller (2012) show that in dynamic models of fertility it is important to allow for such details of the birth history in the state space. To accomplish this and to preserve computational tractability, we might switch to 2-step strategies that rely on conditional choice probabilities (CCPs). By limiting how much of the history belongs in the state space, we can generate stochastic finite dependence which, as noted by Arcidiacono and Miller (2011), makes the CCP approach particularly simple. Alternatively, we can leverage data on age at sterilization and expand the model to allow for this terminal action. Hotz and Miller (1993) show that the CCP approach is particularly powerful in models with terminal actions.

In addition to enhancements to the model and the estimation strategy we envisage a more comprehensive set of counterfactual experiments. Despite failing to reject the null of "no gender bias", it would be interesting to explore what happens to the sex-ratio. Also, it would be interesting to explore some technological and regulatory/institutional variations on the basic experiments. For example, what would happen if this technology increases the chances of having a child of a given gender but it is not 100% accurate. We could explore how results vary for different accuracies. Similarly, one could ask, what if as in MicroSort’s case accuracy differs by gender, with 90% accuracy when seeking a girl and 80% accuracy when seeking a boy. On the institutional side, one could ask what if only "pink" technology is available (i.e. what if the technology is only allowed when seeking a girl)? This could be more relevant for countries with strong preferences for boys. Finally, what if, as in MicroSort’s trials, the technology is only available for "family balancing". This is a policy in which only parents with documented gender imbalance in their offspring (i.e. only those who’ve already had one, two or more children of the same gender and desire to "balance" their families) would be eligible to use the technology.
Finally, it is worth mentioning that given our preliminary results, gender selection could become an efficient tool among reproductive policy options in countries currently exploring ways to increase their fertility. For example, fertility rates in many European countries are below replacement rates and many targeted pro-natalist policies have failed to revert this trend.\textsuperscript{31} Since most European countries may have similar taste for gender variety, a careful, regulated use of gender selection technology targeted to women who would otherwise not take the risk of a second birth could provide a substantial boost to fertility rates. Also given increasing economic burden generated by its One-Child policy, China is exploring ways to relax it. One could imagine a selective use of "pink" technology to allow some parents, especially those with boys, to have a second child. Limiting technology use to select girls only would, at the same time, help balance the sex ratio.

\textsuperscript{31}See, however, Laroque and Salanie (2012), who estimate a large impact of a 150 euro child credit.
References


