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The demand for season of birth

Damian Clarke[1,2] | Sonia Oreffice[2,3] | Climent Quintana-Domeque[2,3]

[1]Department of Economics, Universidad de Santiago de Chile, Santiago, Chile
[2]IZA, Bonn, Germany
[3]Department of Economics, University of Exeter, Exeter, UK

Correspondence
Climent Quintana-Domeque, University of Exeter Business School, Streatham Court, Rennes Drive, Exeter EX4 4PU, UK.
Email: c.quintana-domeque@exeter.ac.uk

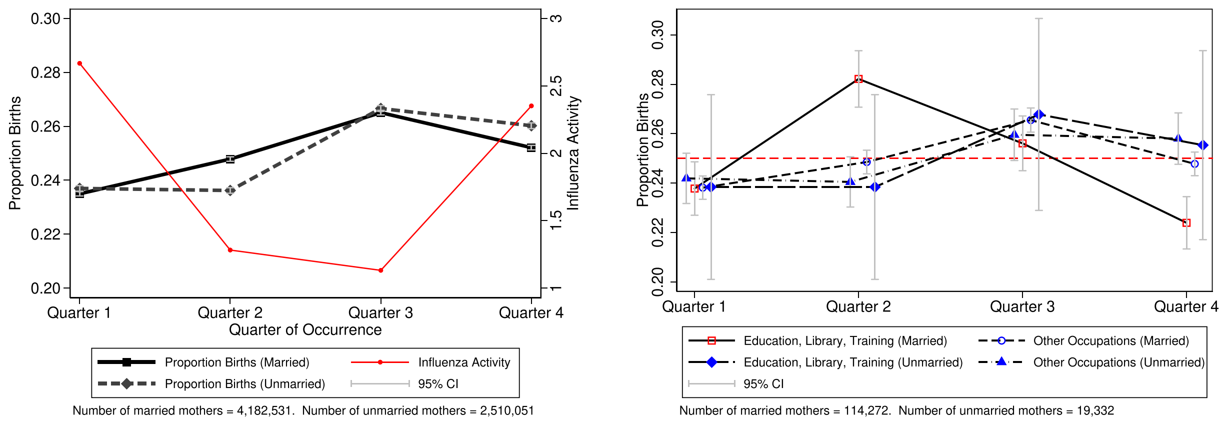
Summary

We study the determinants of season of birth for married women aged 20–45 in the USA, using birth certificate and Census data. We also elicit the willingness to pay for season of birth through discrete-choice experiments implemented on the Amazon Mechanical Turk platform. We document that the probability of a spring first birth is significantly related to mother's age, education, race, ethnicity, smoking status during pregnancy, receiving WIC (Women, Infants & Children) food benefits during pregnancy, prepregnancy obesity, and the mother working in "education, training, and library" occupations; whereas among unmarried women without a father acknowledged on their child's birth certificate, all our findings are muted. A summer first birth does not depend on socioeconomic characteristics, although it is the most common birth season in the USA. Among married women aged 20–45, we estimate the average marginal willingness to pay (WTP) for a spring birth to be 877 USD. This implies a willingness to trade-off 560 grams of birth weight in the normal range to achieve a spring birth. Finally, we estimate that an increase of 1,000 USD in the predicted marginal WTP for a spring birth is associated with a 15 pp (percentage points) increase in the probability of obtaining an actual spring birth.

1 | INTRODUCTION

While the relevance of season of birth has been acknowledged at least since Huntington's (1938) book *Season of Birth: Its Relation to Human Abilities*, it was not until recently that season of birth became prominent in biology, economics, and social sciences more generally. There is now a well-established literature illustrating a variety of aspects that are significantly correlated with season of birth, including birth weight, education, earnings, height, life expectancy, and schizophrenia. Although understanding the channels through which season of birth affects these outcomes still represents a scientific challenge, in the USA winter months are associated with lower birth weight, education, and earnings, whereas spring and summer are found to be "good" seasons (e.g., Buckles & Hungerman, 2013; Currie & Schwandt, 2013).

Using birth certificate and Census data we provide new evidence on season of birth patterns and correlates with demographic and socioeconomic characteristics among married women, which are absent among unmarried women with no paternity acknowledgment on their child's birth certificate, or among those using assisted reproductive technology (ART) procedures. We argue that these can be explained by season of birth being a choice variable subject to economic and biological constraints, when women do plan fertility timing. The plausibility of a demand for season of birth is also documented by the positive average marginal willingness to pay for season of birth and spring in particular, which we estimate using discrete-choice experiments in the Amazon Mechanical Turk platform.



(a) Birth Quarter and Influenza Activity

(b) Birth Quarter and Occupation

FIGURE 1 Births by quarter (married mothers 20–45), influenza activity, and occupation: (a) Birth quarter and influenza activity; (b) Birth quarter and occupation. Both samples consist of all singleton first-born children in the USA born to mothers aged 20–45 in respective data, and all estimates refer to the raw proportion of births due (a) or occurring (b) in each quarter. Part a plots the proportion of births as calculated from the universe of birth certificates from 2005 to 2013. Influenza activity refers to the percent of outpatient visits to healthcare providers for influenza-like illness based on data reported to the CDC's ILINet platform in the years 2009–2013 (first available from 2009). Part b displays actual birth quarter frequency from the American Community Survey, for all mothers who are either the head of the surveyed household or the wife/partner of the head of the surveyed household, and both the mother and the husband/partner work in an occupation with at least 500 workers in the full sample. Women are classified into two groups: those working in the "education, training and library" occupation, and those working in any other occupation. For each group, the proportion of births in each quarter is plotted, along with the 95% confidence interval of this estimate. These values are slightly shifted around each quarter on the plot for ease of understanding. The 95% confidence interval is based on Leamer critical values. The horizontal dashed line indicates equal proportion of births in each quarter [Colour figure can be viewed at wileyonlinelibrary.com]

Plots of first birth prevalence and influenza activity by quarter presented in Figure 1a are consistent with married women choosing a spring birth because their child will be born the farthest from the influenza peak within a year, or summer because there are fewer germs at birth and in the last stage of pregnancy. Conversely, among unmarried mothers with no paternity acknowledgment, fall (Quarter 4) births are more prevalent, while spring (Quarter 2) births are less prevalent, in spite of facing the same influenza activity as married mothers. Moreover, Figure 1b shows that working in particular occupations is correlated with a higher spring birth and lower fall birth prevalence. Thus influenza and the winter disease environment are not sufficient to fully explain the observed birth seasonality.

Using US Vital Statistics data on all first singleton births to married women aged 20–45, we show that the prevalence of spring births is related to mother's age in a humped-shaped fashion, positively related to education and being white, and negatively related to being Hispanic, smoking, and receiving food benefits during pregnancy, conditional on gestation week, state, and year fixed effects. However, maternal socioeconomic characteristics do not correlate with the probability of having a baby in summer, despite summer being the most common birth season in the USA. When focusing on the placebo group of unmarried mothers with no paternity acknowledgment on their child's birth certificate, our seasonal patterns are muted, consistent with the idea that the children of unmarried women with no stable partner or long-term relationship are less likely to be planned, and thus it is less likely that their season of birth is chosen (Almond & Rossin-Slater, 2013; Rossin-Slater, 2017). Indeed, in the USA, unmarried women are reported to be more than twice as likely to have unwanted pregnancies than married women (Finer & Zolna, 2016; Mosher, Jones, & Abma, 2012).

We then examine the interaction of a first singleton child's season of birth with his or her mother's occupation using data from the American Community Survey. Our findings reveal that in professions allowing more flexibility in taking time off work and those that have summer breaks (e.g., among teachers), married mothers are additionally more likely to choose spring births but *not* summer births, and this holds conditional on age, education, race, ethnicity, and state and year fixed effects. This is consistent with the evidence in Figure 1b.

Inspired by Buckles and Hungerman (2013), who recognize that a thorough investigation of preferences for birth timing is an open and fertile challenge for future work, we devised and ran a series of discrete-choice experiments in the Amazon Mechanical Turk market place in September 2016 and May 2018, to elicit the willingness to pay for season of birth in two different quarters of the year.[1] We estimate the average marginal willingness to pay for a spring birth to be 620 USD. We also find that the average marginal willingness to pay (WTP) is larger (about 877 USD) among married mothers aged 20–45, our main group of analysis in the birth certificate and Census data, whereas among respondents who do not intend to have children the average marginal WTP is much smaller (about 455 USD) and not statistically different from zero, which provides an interesting placebo. Exploring heterogeneity by number of children, we find that our estimate is driven by married mothers aged 20–45 with two or more children (1,100 USD).

Using a mixed logit to allow for preference heterogeneity among married mothers aged 20–45 in the M-Turk data, we estimate the marginal WTP for spring births for each married mother aged 20–45. We then predict the estimated marginal WTP for spring births using maternal characteristics in the same M-Turk data. Assuming transportability from M-Turk to birth certificate data, we use the estimated coefficients on the maternal characteristics to predict the marginal WTP for each married mother aged 20–45 in the latter data. We then investigate the relationship between predicted marginal WTP and spring births in the birth certificate data. We find that a 1,000 USD increase in the predicted marginal WTP for a spring birth is associated with an increase in the actual probability of giving birth in spring of about 15 pp. This finding suggests that average elicited M-Turk responses do correlate with actual behavior.

Our estimated seasonality gaps, between −0.5 pp (Hispanic vs. non-Hispanic) and 0.9 pp (received food benefits during pregnancy) in the birth certificate data, and 5 pp by occupation in the Census data, are sizable. Buckles and Hungerman (2013) report a 1 pp difference in teenage mothers and a 2 pp difference in unmarried or nonwhite mothers between January births and May births, and they interpret these gaps as "strikingly large" compared to the estimated effects of welfare benefits on nonmarital childbearing (Rosenzweig, 1999) or unemployment on fertility (Dehejia & Lleras-Muney, 2004). Our estimates of the value of a spring birth, 877 USD or 560 grams of birth weight, are nonnegligible, which supports our contention that there is indeed a demand for season of birth.

As noted by Leamer (1978), in very large samples almost any hypothesis of the sort $\beta = 0$ is rejected, and meaningful hypothesis testing requires the significance level to be a decreasing function of sample size: Classical hypothesis testing at a fixed level of significance increasingly distorts the interpretation of the data against a null hypothesis as the sample size grows. By raising the critical values of test statistics with the sample size, the benefits of increased precision are more equally allocated between reduction in Type I and Type II errors (Deaton, 1997). Leamer's suggestion is to adjust the critical value for t tests as follows: Instead of using the standard tabulated values, the null hypothesis is rejected when the absolute value of the calculated t exceeds the square root of the logarithm of the sample size; that is, reject $H_0 : \beta = 0$ if and only if $|t_{\text{act}}| > \sqrt{\log(N)}$.[2] This paper follows such an approach for all confidence intervals, statistical significance thresholds and hypothesis testing.

Recent work by Barreca, Deschenes, and Guldi (2018) documents that short-term shifts in conception weeks in response to very hot days result in birth rate declines 8–10 months later and increases in summer births. However, their paper does not consider preferences for season of birth or how maternal characteristics are related to birth seasonality or spring in particular. Currie and Schwandt (2013) explain the first quarter of birth disadvantage through the negative impact of the disease environment on birth weight and gestational weeks in cold months (influenza at birth drives seasonality in gestational length), whereas Buckles and Hungerman (2013) emphasize the role of maternal characteristics in shaping the later socioeconomic disadvantage of winter-borns, showing that their mothers are less educated, less likely to be married or white, and more likely to be teenagers. They also show that seasonality appears to be driven by wanted births—there is no seasonality in maternal characteristics among unwanted births, as revealed by the data from the National Survey of Family Growth. In France, Régnier-Loilier (2010) finds that "the primary school teachers' April peak is almost entirely due to seasonal birth strategies," although his data, the French registry of live births, do not report mother's occupation for 40% of the births, and primary school teachers represent a small selected group of women working in the educational sector. However, none of these studies considers selective preferences for spring versus summer births by maternal characteristics, marital status, and occupation in particular, or estimates the willingness to pay for season of birth.

There is also a literature on "exact" birth timing that analyzes the joint decision of parents and physicians to alter the delivery of an already existing pregnancy in response to nonmedical incentives. Birth timing does not happen systematically before school-eligibility cutoff dates (Dickert-Conlin & Elder, 2010), while Dickert-Conlin and Chandra (1999) and LaLumia, Sallee, and Turner (2015) report that parents may move expected January births backwards to December to gain

[1]We thank an anonymous referee for the suggestion to run an additional survey in a different season.

[2]The actual derivation in Leamer is formulated in terms of F tests. Leamer (1978, pp. 114–115) shows that the critical value for an F test is $\left[\frac{N-K}{P}\right]\left(N^{\frac{P}{N}}-1\right)$, where P is the number of restrictions and K is the number of parameters. Moreover, this critical value can be approximated by $\log(N)$. In this paper we use the exact rather than approximate values when conducting tests.

tax benefits. Schulkind and Shapiro (2014) also explore the infant health effects and mechanisms of these tax shifts. Fewer births are documented on holidays and weekends (Gould, Qin, Marks, & Chavez, 2003), medical professional meeting dates (Gans, Leigh, & Varganova, 2007), and less auspicious dates (Almond, Chee, Sviatschi, & Zhong, 2015). This body of evidence clearly shows that parents may be willing and able to manipulate birth timing, but this represents a choice made well *after* conception occurs. Our analysis departs from this literature, since we study a choice made *before* conception occurs.

In what remains of this paper, Section 2 describes the data sources. Section 3 presents the analysis of the correlates of season of birth using birth certificate and census data. Section 4 provides the analysis of willingness to pay for season of birth. Section 5 concludes the paper.

2 | DATA SOURCES

2.1 | Birth certificate data

Data on all births occurring each year in the USA are collected from birth certificate records, and are publicly released as the National Vital Statistics System (NVSS). All registered births in all states and the District of Columbia are reported from 1984 onwards. In total, more than 99% of births occurring in the country are registered (Martin, Hamilton, Osterman, Curtin, & Mathews, 2015). Birth certificates have gone through two important revisions in the variables reported: one in 1989 and the other in 2003. Prior to 2003, all states had adopted the 1989 revision of the birth certificate. From 2003 onwards, states began adopting the 2003 revision; however, the year of adoption varied by state. The 2003 revision added additional questions and changed the coding of various questions, such as smoking and maternal education. When changing questions, particularly in the case of maternal education, the correspondence in reported levels in the 1989 and 2003 revisions is not one to one. Our analysis period starts with the 2005 file rather than the 2003 file because it is only from 2005 onwards that maternal education is reported for all respondents.[3]

The birth certificate data record important information on births and their mothers. For the mother, this includes age, race, ethnicity, marital status, education, smoking status during pregnancy, and, since 2009, ART use, whether the mother received WIC (Women, Infants & Children) food benefits during pregnancy, height, and prepregnancy weight.[4] For the newborn, in addition to place and time of birth and paternity acknowledgment, measures include birth parity, singleton or multiple births status, gestational length (in weeks), birth weight, and 1- and 5-minute APGAR scores.

Our main estimation sample consists of the years 2005–2013, and we retain all singleton first-births to married mothers aged 20–45 who are issued an updated birth certificate with available education, smoking status, and gestational length: 4,184,932 first births, 4,182,531 of which have gestation length recorded—that is, for whom conception month is known. Season of birth is defined as the *expected* (intended) season of birth, which we compute combining information on the month of birth and gestational length. In practice, and following Currie and Schwandt (2013), month of conception is calculated by subtracting the rounded number of gestation months (gestation in weeks $\times$ 7/30.5) from month of birth.[5] Hence we focus on the *planning* of season of birth—that is, the decision to conceive.[6]

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[3] In 2003, maternal education is not reported for states which have adopted the updated birth certificate ("Where data for the 1989 and 2003 certificate revisions are not comparable (e.g., educational attainment of the mother), data for Pennsylvania and Washington are excluded from the national totals for 2003"); Centers for Disease Control (2003, p. 10). In 2004, a small number of observations do not have maternal education reported ("For the two states which revised in 2004, but after January 1, data which are not comparable across revisions are excluded from all tabulations …"); Centers for Disease Control (2004, p. 5).

[4] The question on WIC benefits is: "Did you receive WIC food for yourself because you were pregnant with this child?" We use height and prepregnancy weight to construct prepregnancy body mass index (BMI) and the standard BMI categories: Underweight (BMI $<$ 18.5), Normal Weight (18.5 $\leq$ BMI $<$ 25), Overweight (25 $\leq$ BMI $<$ 30), and Obese (BMI $\geq$ 30). We restrict our sample to mothers with a BMI between 16 and 40.

[5] Gestation weeks are converted to months by multiplying the weeks by the number of days in a week (7) and then dividing by the average number of days in a month (30.5). That is:

$$\text{gestation in months} = \text{gestation in weeks} \times \frac{\text{days/week}}{\text{days/month}}.$$

One could also make this calculation using

$$\text{gestation in months} = \text{gestation in weeks} \times \frac{\text{month/year}}{\text{weeks/year}}.$$

In either case, the result is very similar. For example, in the range of gestation weeks from 35 to 40 weeks, the number of months is identical up to at least the first decimal point. We use the day method simply following Currie and Schwandt (2013).

[6] Using *actual* or *expected* season of birth is immaterial for our findings.

We then focus on the placebo group of unmarried women with no paternity acknowledgment of their child, based on the logic that women in this group are less likely to plan fertility and specifically conceptions, thus not choosing season of birth. We consider unmarried mothers aged 20–45 with no paternity acknowledgment of their child (first births: 479,575; 478,924 with available information on gestational length).

2.2 | Census data

In order to investigate the role of mother's occupation, unavailable in the US birth certificate data, in explaining season of birth, we supplement our previous analysis with the American Community Survey (ACS), conducted by the United States Census Bureau on a representative 1% of the US population every year (Ruggles, Genadek, Goeken, Grover, & Sobek, 2015). Quarter of birth has been continuously available in the ACS since 2005. Along with demographic and socioeconomic characteristics of women, we observe their labor market outcomes and specifically occupation, which is coded using the standard Census occupation codes and defined as the individual's primary occupation for those who had worked within the previous 5 years.

We use data from 2005 to 2014 and focus on married women aged 20–45 who are either the head of the household or spouse of the head of the household, and have a first singleton child who is *at most* 1 year old. Given that Census data do not provide gestational length, season of birth is defined as the *actual* quarter of birth, not the *expected* one. We retain only women who had worked within the previous 5 years in nonmilitary occupations where each occupation must have at least 500 women over the entire range of survey years.[7]

2.3 | Amazon mechanical turk data

We collect data on preferences for season of birth, alongside respondents' demographic and socioeconomic characteristics, devising and running a series of discrete-choice experiments to elicit the willingness to pay for season of birth. All this information was obtained through two surveys administered on the Amazon Mechanical Turk platform, which is an online labor market with hundreds of thousands of "workers". Mechanical Turk "workers" are increasingly relied upon in cutting-edge economic research (Berinsky, Huber, & Lenz, 2012; Francis-Tan & Mialon, 2015; Kuziemko, Norton, Saez, & Stantcheva, 2015).

We published a "HIT" (Human Intelligence Task) request for 2,000 "workers" to complete a short survey, about 6 minutes long, and paid 1.10 USD (which corresponds to a pay rate of about 10 USD per hour), on a Monday in September 2016. We devised the following requirements to ensure the validity of our data. We restricted eligibility to those with approval rates above 95% and with more than 100 tasks already completed, while including an attention-check question and asking for the education level at the beginning and end of the survey to check for consistency. We also dropped those who finished the survey in less than 2 minutes and those who had an IP address which suggested that they were based outside of the USA (5.05% of respondents were dropped with all these checks, mainly because their geographic IP was outside of the USA: 3.7%). In addition, the survey was designed in such a way that respondents needed to answer each and every question to be able to move to the following screen and thus complete the survey. Respondents were clearly instructed that payment was contingent on submitting a numerical code visible only at completion. All "workers" needed to have a US social security number to be able to register in the Mechanical Turk platform as "workers" since 2009. However, we took the additional precaution of launching the survey at 9.00 am East Coast time, to increase the likelihood that respondents were actually residing in the USA rather than in Asia, for instance, since all our analyses were based on US data. By 2.13 pm, 2,000 respondents had completed our task.

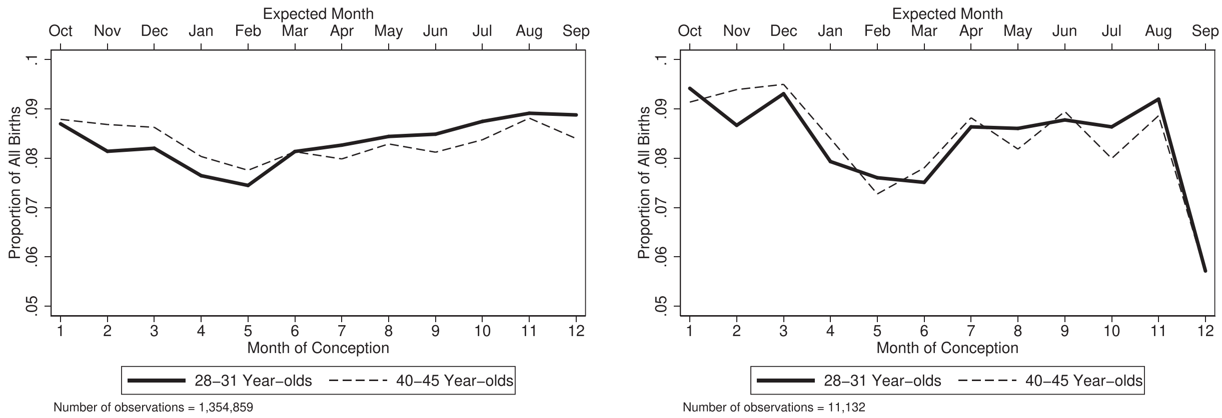
We then ran the same exercise in a different season of the year, on a Monday in May 2018, preventing former respondents participating in this new survey. We had run a pilot a few months before our first survey, and we prevented the same participants taking our surveys (2016 and 2018) to avoid priming effects.

3 | SEASON OF BIRTH CORRELATES

3.1 | Main sample: Married mothers

Table A1 in the online Supporting Information Appendix displays summary statistics for married mothers aged 20–45 (panel a) and their first singleton births born between 2005 and 2013 (panel b). The average mother's age in our group is 28.6, 5% are black, 83% are white, 16% are Hispanic, 63% have at least some college and 3.5% report having smoked during

[7]We exclude women who are in the military, in a farm household, or currently in school. The very small number of observations of households containing two women have been excluded.



(a) Proportion of Conceptions in Each Month

(b) Proportion of Conceptions (ART Only)

FIGURE 2 First birth prevalence by month, age group, and ART usage (married mothers). (a) Proportion of conceptions in each month; (b) proportion of conceptions (ART only). Month of conception is calculated by subtracting the rounded number of gestation months (gestation in weeks × 7/30.5) from month of birth. Each line presents the proportion of all first, singleton births conceived in each month for the relevant age group (28–31 or 40–45) among all married first-time singleton mothers, contained in birth certificate data from the period 2005–2013

pregnancy. In addition, for births occurring after 2009, we have information on whether those were conceived through the use of assisted reproductive technology (1%), whether the mother received food benefits during pregnancy (20%), and her prepregnancy BMI (the average mother being nearly overweight: 24.75). The average baby has a gestational length of 39 weeks and 8.5% are born prematurely (<37 weeks). The season with the highest prevalence is summer (Quarter 3: 0.27), followed by spring (Quarter 2: 0.25), fall (Quarter 4: 0.25) and winter (Quarter 1: 0.23).

In Figure 2a we can see that "younger" (28–31) mothers are more likely to have their first birth in summer and spring than "older" (40–45) mothers, while the former are less likely to give birth in winter and fall than the latter (p-values on tests for the equality of means in each quarter by age group are < 0.001 in each case).[8] If "younger" and "older" mothers have the same preferences for season of birth, this pattern is suggestive of the biological constraints that "older" mothers face. Of course, this biological pattern may be reinforced by different preferences—that is, if "older" mothers are less concerned about the season of birth and more about getting pregnant than "younger" mothers. If women undergoing ART procedures to achieve their first birth cannot and do *not* choose season of birth, we should not expect to find such a discrepancy between "younger" (28–31) and "older" (40–45) mothers with births achieved through the use of ART procedures. This is exactly what we find in Figure 2b: the season of birth prevalence is unrelated to their age (the majority of women undergoing ART are older than 35). The bold (28–31) and dashed (40–45) lines cross several times (p-values on tests for the equality of means in each quarter by age group are 0.53, 0.94, 0.22, and 0.46 for Quarters 1–4, respectively).[9] This evidence indicates that when women can and want to choose season of birth, observed seasonality patterns are different.

We now investigate the relationship between the proportions of first births in spring (Quarter 2) and summer (Quarter 3) and mother's characteristics. In Figure 3 we find a weak negative relationship between the prevalence of summer first births and mother's age; there seems to be a humped-shaped relationship between the prevalence of spring first births and mother's age: This nonmonotonicity is consistent with selection and biological effects, a point that we will discuss further below.

In Table 1 we investigate the determinants of the probability of having a first birth in spring (Quarter 2). In column (1) we regress a dummy variable of spring (=1 if first birth in spring, =0 otherwise) against mother's age and its square, and confirm the quadratic relationship described in Figure 3. In column (2) we can see that the relationship is robust to controlling for year and state fixed effects. Column (3) includes education (=1 if the mother has at least some college, =0 otherwise), smoking during pregnancy (=1 if the mother smoked during pregnancy, =0 otherwise), black (=1 if the mother is black, =0 otherwise), white (=1 if the mother is white, =0 otherwise), Hispanic (=1 if the mother is Hispanic, =0

[8]The absolute values of the actual t statistics are 4.69 for Q1, 5.27 for Q2, 6.19 for Q3, and 7.00 for Q4. The Leamer critical value is 3.76.

[9]The drop in conceptions in December is in line with the seasonality of treatment availability in ART clinics, which in many cases do not offer complex fertility treatments such as IVF (in vitro fertilization) or embryo transfers in December due to Christmas closure and the daily attention and last-minute changes that these treatments require.

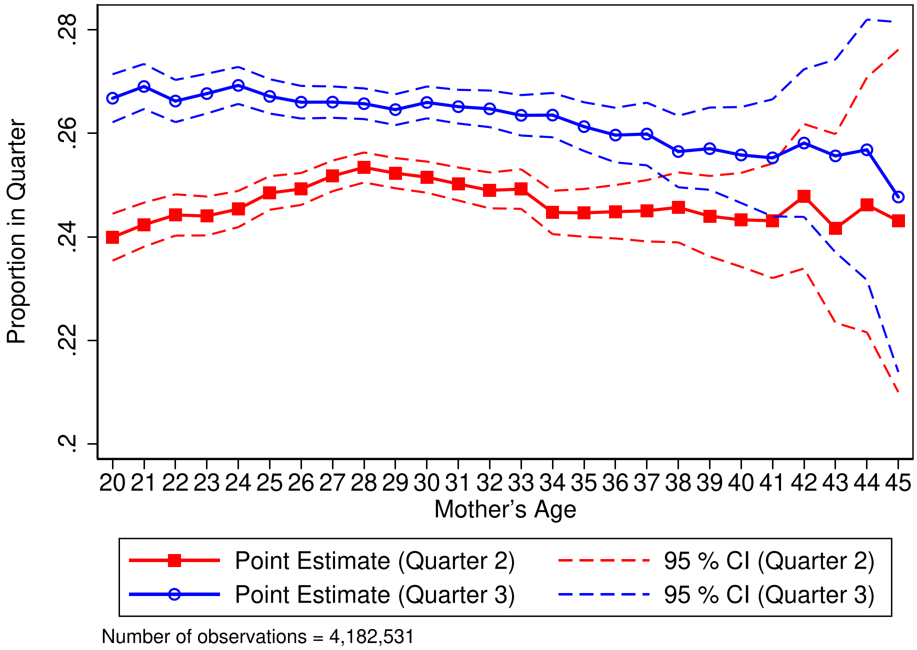


FIGURE 3 Prevalence of Quarter 2 and Quarter 3 by age (married mothers, 20–45). (a) Coefficients and standard errors are estimated by regressing Quarter 2 or Quarter 3 on dummies of maternal age with no constant. The sample consists of all first-born singleton children contained in birth certificate data from 2005 to 2013 born to married mothers aged 20–45 for whom education, smoking during pregnancy, and gestational length of child's birth are recorded. 95% CI refers to the confidence intervals and are calculated using Leamer/Schwartz/Deaton critical values adjusting for sample size [Colour figure can be viewed at wileyonlinelibrary.com]

otherwise), and gestation week fixed effects. The nonmonotonic relationship is still present. We also observe that women with at least some college and white women are 0.8 and 0.9 pp more likely to have their first birth in spring than their respective counterparts; women who smoked during pregnancy and Hispanic women are, respectively, 1 and 0.8 pp less likely to have their first birth in spring than their respective counterparts.

Restricting our analysis to the births that occurred between 2009 and 2013, column (4), does not affect our results. Finally, in column (5), we include information that is only available from 2009 onwards, namely whether the mother received food benefits in pregnancy, mother's prepregnancy body mass index, and whether the birth was achieved through ART. The magnitudes on the coefficients of the variables included in previous columns are quite similar, albeit slightly smaller. In addition, we find that women who received food benefits in pregnancy are 0.9 pp less likely to have their first birth in spring than their counterparts, and those who were obese in the prepregnancy period were 0.3 pp less likely to have their first birth in spring. Controlling for state-specific linear trends and unemployment rate at season of conception is immaterial for our findings (see Table A2 in the Supporting Information Appendix).[10]

In Table 2 we conduct exactly the same analysis but for summer (Quarter 3), so that the dependent variable now equals 1 if the birth happens in summer, and 0 otherwise. Interestingly, with the exception of ethnicity, race, and ART usage indicators, none of the factors under consideration is statistically significant.[11] The ART usage finding is driven by the drop in December conceptions documented in Figure 2b: Once we exclude these conceptions, neither ethnicity nor ART usage matters (see Table A5 in the Supporting Information Appendix).[12] Black and white mothers exhibit a positive significant correlation with summer births; Asian and Native Americans (our omitted group) may feel the festive season of Thanksgiving and Christmas differently, or respond differently to winter.

The findings in Table 1 seem to confirm that the humped-shaped relationship between the prevalence of spring first births and mother's age is due to selection and biological effects. On one hand, "older" mothers tend to be positively selected (in terms of socioeconomic characteristics),[13] so that they are more likely to target spring; on the other hand, "older" mothers are more likely to be biologically constrained. Interestingly, the spring birth maximizing age—the optimal age for having a spring baby, the turning point of the mother's age quadratic—changes from about 30 in columns (1) and (2) to about 25 in column (5), where socioeconomic selection into pregnancy is accounted for, in addition to year and state

[10]Table A3 in the Supporting Information Appendix estimates a logit rather than a linear regression: Results are virtually the same.
[11]Table A4 in the Supporting Information Appendix estimates a logit rather than a linear regression: Results are virtually the same.
[12]Dropping the age squared term results in a statistically significant coefficient for age, but with a very small magnitude −0.0003 (see column (6)), consistent with the weak negative relationship described in Figure 3. Once again, controlling for state-specific linear trends and unemployment rate at season of conception does not change our findings (see Table A6 in the Supporting Information Appendix).
[13]For example, the correlation coefficient between having at least some college education and maternal age is 0.27 and remains large and positive even when focusing on older ages when educational attainment is complete, and that between smoking and maternal age is −0.09 (older mothers are less likely to smoke) in our main sample of married first-time mothers aged 20–45. Both relationships are statistically significant using Leamer's criterion.

TABLE 1 Season of birth correlates: Quarter 2 (married mothers, 20–45)

	(1) Quarter 2	(2) Quarter 2	(3) Quarter 2	(4) Quarter 2	(5) Quarter 2
Mother's age (years)	0.006 [a]	0.005 [a]	0.003 [a]	0.003 [a]	0.002
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Mother's age^2/100	−0.010 [a]	−0.009 [a]	−0.006 [a]	−0.006 [a]	−0.004 [a]
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Some college +			0.008 [a]	0.008 [a]	0.006 [a]
			[0.001]	[0.001]	[0.001]
Smoked in pregnancy			−0.009 [a]	−0.008 [a]	−0.007 [a]
			[0.001]	[0.002]	[0.002]
Black			−0.003	−0.004	−0.003
			[0.001]	[0.001]	[0.001]
White			0.009 [a]	0.009 [a]	0.008 [a]
			[0.001]	[0.001]	[0.001]
Hispanic			−0.008 [a]	−0.007 [a]	−0.005 [a]
			[0.001]	[0.001]	[0.001]
Received WIC food in pregnancy					−0.009 [a]
					[0.001]
Prepregnancy underweight (BMI < 18.5)					−0.002
					[0.001]
Prepregnancy overweight (25 ≤ BMI < 30)					0.000
					[0.001]
Prepregnancy obese (BMI ≥ 30)					−0.003 [a]
					[0.001]
Did not undergo ART					−0.002
					[0.003]
Observations	4,182,531	4,182,531	4,182,531	2,665,350	2,665,350
F test of age variables	101.924	84.315	44.868	28.327	31.809
Leamer critical value (*F*)	15.246	15.246	15.246	14.795	14.795
Spring birth maximizing age	30.09	29.85	28.08	27.83	25.26
State and year FE		Y	Y	Y	Y
Gestation FE			Y	Y	Y
2009–2013 only				Y	Y

Note. All singleton, first−born children of married 20− to 45−year−old mothers are included. All births occurring from 2005 to 2013 are included unless otherwise specified in column notes. The omitted baseline race in each case is Asian/Native American. *F* test of age variables refers to the test that the coefficients on mother's age and age squared are jointly equal to zero. The critical value for rejection of joint insignificance is displayed below the *F* statistic. Leamer critical values refer to Leamer/Schwartz/Deaton critical 5% values adjusted for sample size. The Leamer critical value for a *t* statistic is 3.905 in columns (1)–(3) and 3.846 in columns (4) and (5). Spring birth maximizing age calculates the turning point of the mother's age quadratic. Heteroskedasticity robust standard errors are reported in parentheses. [a]Significance based on Leamer criterion at 5%.

fixed effects. Once this is taken into account, we observe that the spring birth maximizing age for the first child decreases: Younger women are less biologically constrained and hence this age decreases.

Moreover, a clear asymmetry arises between the findings in Tables 1 and 2: Observable maternal factors, other than race and ethnicity, cannot explain the probability that a first birth occurs in summer, but do partially explain the probability that a first birth occurs in spring. This suggests that while first births in spring cannot be taken as being “as good as” randomly assigned, consistent with being the result of parental choices, the occurrence of summer births is unrelated to observable maternal characteristics, conditional on race and ethnicity. Conceptions in the holiday season of Thanksgiving and Christmas seem to be popular regardless of maternal socioeconomic characteristics.

3.2 | Placebo sample: Unmarried mothers with no paternity acknowledgment of their child

If season of birth were a choice variable, then we would expect it to be driven by the group of mothers who are likely to plan fertility, have wanted pregnancies, and time their births. Unmarried women in the USA are reported to be more than twice as likely to have unwanted pregnancies than married women (Finer & Zolna, 2016; Mosher et al., 2012). In

TABLE 2 Season of birth correlates: Quarter 3 (married mothers, 20–45)

	(1) Quarter 3	(2) Quarter 3	(3) Quarter 3	(4) Quarter 3	(5) Quarter 3
Mother's age (years)	0.001	0.001	0.001	0.001	0.001
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Mother's age^2 / 100	-0.003[a]	−0.002	−0.003	−0.003	−0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Some college +			0.001	0.001	0.001
			[0.001]	[0.001]	[0.001]
Smoked in pregnancy			−0.001	0.000	0.000
			[0.001]	[0.002]	[0.002]
Black			0.010	0.011[a]	0.011[a]
			[0.001]	[0.001]	[0.001]
White			0.008[a]	0.009[a]	0.009[a]
			[0.001]	[0.001]	[0.001]
Hispanic			0.003[a]	0.004[a]	0.003[a]
			[0.001]	[0.001]	[0.001]
Received WIC food in pregnancy					0.001
					[0.001]
Prepregnancy underweight (BMI < 18.5)					−0.002
					[0.001]
Prepregnancy overweight (25 ≤ BMI < 30)					0.001
					[0.001]
Prepregnancy obese (BMI ≥ 30)					0.000
					[0.001]
Did not undergo ART					0.027[a]
					[0.003]
Observations	4,182,531	4,182,531	4,182,531	2,665,350	2,665,350
F test of age variables	77.885	80.983	64.758	42.519	30.502
Leamer critical value (*F*)	15.246	15.246	15.246	14.795	14.795
Summer birth maximizing age	20.83	18.4	19.92	20.57	19.45
State and year FE		Y	Y	Y	Y
Gestation FE			Y	Y	Y
2009–2013 only				Y	Y

Note. All singleton, first-born children of married 20- to 45-year-old mothers are included. All births occurring from 2005–2013 are included unless otherwise specified in column notes. The omitted baseline race in each case is Asian/Native American. *F* test of age variables refers to the test that the coefficients on mother's age and age squared are jointly equal to zero. The critical value for rejection of joint insignificance is displayed below the *F* statistic. Leamer critical values refer to Leamer/Schwartz/Deaton critical 5% values adjusted for sample size. The Leamer critical value for a *t* statistic is 3.905 in columns (1)–(3) and 3.846 in columns (4) and (5). Summer birth maximizing age calculates the turning point of the mother's age quadratic. Heteroskedasticity robust standard errors are reported in parentheses. [a]Significance based on Leamer criterion at 5%.

particular, unmarried mothers with no paternity acknowledgment of their child—who lack a stable relationship with the person with whom they conceive their child—should not exhibit any birth seasonality correlations with maternal characteristics if these patterns are driven by a demand for season of birth.[14]

Table A7 in the Supporting Information Appendix shows that births to this type of mothers tend to be concentrated in the second part of the year, first summer (0.27) and then fall (0.26).[15] This pattern is very different from the one observed among married mothers (Table A1). We do not find any differences in birth prevalence between "younger" and "older" women, unlike that among married women (Figure A2), suggesting that among this group of women season of birth is

[14]Considerable discussion of paternity establishment procedures in the USA is provided in Rossin-Slater (2017), and a description of paternity acknowledgment in microdata is available in Almond and Rossin-Slater (2013). We note that the period under study in our data is entirely after the rollout of the in-hospital voluntary paternity establishment (IHVPE) reforms described in Rossin-Slater (2017).

[15]We explore the possibility that selective survival among those live births occurring to unmarried women depends on the month of conception. In particular, unmarried women with no paternity acknowledgment of their child have fewer resources to cushion the negative effects of cold weather on their health and that of their babies in the womb. A differential selective survival pattern by marital status can be observed in Figure A1 in the Supporting Information Appendix, where we plot the evolution of fetal deaths by month of occurrence. While the number of fetal deaths is more or less constant over the year among married mothers, this is lower in the second half of the year among unmarried women with no paternity acknowledgment.

not a choice variable. Figure A3 plots the fraction of births in spring and summer by mother's age. There is neither a humped-shaped relationship between spring prevalence and mother's age nor a negative relationship between summer prevalence and mother's age. If unmarried women with no paternity acknowledgment of their child are not choosing season of birth, the distribution of births by quarters will be the same for “younger” and “older” women, even if older women are less likely to conceive.

Supporting Information Tables A8 and A9 show that none of the factors under analysis explains season of birth. If anything, both being born in spring or summer is “as good as” randomly assigned among unmarried women with no paternity acknowledgment of their child, and summer births are the most popular, suggesting a mechanical holiday effect for *all* women. This is consistent with season of birth not being chosen by this group of women, which is the group less likely to plan pregnancies and pregnancy timing.

Finally, the analysis of second births reveals stronger patterns among married women aged 20–45 and the same absence of patterns among unmarried women without paternity acknowledgment, supporting our contention that there is a demand for season of birth when births are planned.[16]

These findings have observable implications in the population of mothers who give birth at different seasons of the year. Spring is the season in which unmarried women with no paternity acknowledgment of their child make up the lowest proportion of all births, whereas married women make up the largest proportion of births among all births. There is thus a relative shortfall of unmarried mothers with no paternity acknowledgment of their child in the population of spring births compared to what would be expected if births were evenly spaced throughout the year, and a relative glut in all other seasons. Married mothers, on the other hand, have a relative glut during spring and summer, and a shortfall during winter and fall. In Supporting Information Table A13, we consider how birth patterns differ from what would be observed if the full population followed the seasonality patterns of unmarried women with no paternity acknowledgment. These calculations suggest that planning has considerable bite; for example, on average in each year we consider, we observe 6,300 additional births in spring to married first-time mothers (or 56,700 more spring births occurring in this group over the period 2005–2013). As we can see, the projections show that the main difference between our sample of married women and the sample of unmarried women with no paternity acknowledgment is a much higher prevalence of spring (Quarter 2) births and a much lower prevalence of fall (Quarter 4) births. Much less movement is observed in terms of winter (Quarter 1) and summer (Quarter 3) birth prevalence shifts, confirming that summer is the most popular season, while winter is not, regardless of the type of mother.[17]

3.3 | Census sample

If season of birth is a choice variable, it may be related to mother's occupation, if only because certain jobs allow more flexibility in taking time off work in certain seasons or having summer breaks; this is particularly relevant in the USA, given the very limited maternity leave provisions available.

In Table 3 we investigate the importance of occupation in explaining the probability of having a first birth in spring (Quarter 2), column (1), and summer (Quarter 3), column (2), including the two-digit occupational dummy variables from the Census classification.[18] Our findings reveal that women in “education, training and library” occupations are 5 pp more likely to have their first birth in spring than women in “arts, design, entertainment, sports and media” (the omitted base category) occupations. We do not find any other statistically significant relationship between mother's occupation and season of birth. Moreover, and consistent with our findings from Table 2, mother's occupation does not play any role in explaining summer first births: None of the occupational coefficients is either individually significant or jointly significant ($F = 1.239 < 1.587$).[19] It seems that women in “education, training and library” occupations are much more likely to time their births in the spring to have maternity leave before the beginning of their summer break, thus maximizing their time home with the baby as well as the time the baby spends developing and growing before her first winter comes. Table A16 shows that occupation cannot explain the season of birth patterns of unmarried women. In addition, Table A17 shows that our finding that women in “education, training and library” occupations are 5 pp more likely to have their first birth in

[16]Figures A4 and A5, and Tables A10, A11, and A12 in the Supporting Information Appendix, replicate our analysis for second births among married women aged 20–45.

[17]We note that these projections are based on using unmarried mothers with no paternity acknowledgment as a counterfactual group. While this group may contain individuals who do plan birth, it seems likely that this proportion is relatively small, and this counterfactual allows us to largely isolate seasonality due to the demand for season of birth, rather than other cyclical patterns.

[18]Table A14 in the Supporting Information Appendix contains the descriptive statistics for the ACS sample. All occupation codes refer to IPUMS `occ2010` codes, which are available at: https://usa.ipums.org/usa/volii/acs_occtooccsoc.shtml.

[19]Table A15 in the Supporting Information Appendix estimates a logit rather than a linear regression: Results are virtually the same.

TABLE 3 Season of birth correlates in ACS (married mothers, 20–45)

	(1) Quarter 2	(2) Quarter 3
Mother's age	0.008	0.002
	[0.003]	[0.003]
Mother's age^2 / 100	−0.013	−0.004
	[0.005]	[0.006]
Some college +	0.013	−0.011
	[0.005]	[0.005]
Black	0.015	0.007
	[0.010]	[0.010]
White	0.013	0.011
	[0.006]	[0.006]
Hispanic	−0.008	−0.009
	[0.007]	[0.007]
Architecture and Engineering	0.010	0.002
	[0.016]	[0.018]
Building and Grounds Cleaning and Maintenance	0.028	−0.020
	[0.019]	[0.019]
Business Operations Specialists	0.026	0.003
	[0.012]	[0.012]
Community and Social Services	0.040	−0.016
	[0.013]	[0.013]
Computer and Mathematical	0.029	−0.004
	[0.014]	[0.014]
Education, Training, and Library	0.049[a]	−0.014
	[0.010]	[0.010]
Financial Specialists	0.027	−0.004
	[0.012]	[0.012]
Food Preparation and Serving	0.029	0.001
	[0.013]	[0.013]
Healthcare Practitioners and Technical	0.018	0.007
	[0.010]	[0.010]
Healthcare Support	0.011	−0.013
	[0.013]	[0.013]
Legal	0.009	−0.001
	[0.014]	[0.014]
Life, Physical, and Social Science	0.018	−0.006
	[0.015]	[0.015]
Management	0.022	0.004
	[0.010]	[0.011]
Office and Administrative Support	0.021	−0.004
	[0.010]	[0.010]
Personal Care and Service	0.036	−0.009
	[0.012]	[0.012]
Production	0.014	−0.011
	[0.015]	[0.016]
Protective Service	0.055	−0.024
	[0.024]	[0.023]

(*Continues*)

spring holds conditional on husband's occupation too, but the latter is not relevant in explaining birth seasonality: None of the husband's occupational coefficients is either individually significant or jointly significant ($F = 0.979 < 1.517$). Given the strong positive correlation between "teachers" and spring births among married women, this evidence suggests that season of birth is a choice variable.

All in all, our estimated seasonality gaps are sizable, even more so given that our seasonality gaps are obtained within a more homogeneous group of mothers (married, nonteenage) than Buckles and Hungerman (2013). In addition, these seasonality gaps may represent lower bounds of the actual relationship of mothers' characteristics and birth seasonality,

TABLE 3 Continued

	(1) Quarter 2	(2) Quarter 3
Sales	0.012	−0.002
	[0.010]	[0.011]
Transportation and Material Moving	0.038	−0.038
	[0.022]	[0.020]
Observations	108,243	108,243
F test of mother's occupation dummies	3.227	1.239
F test of age variables	2.835	0.608

Note. Sample consists of all singleton first-born children in the USA born to married mothers aged 20–45 included in 2005–2014 ACS data, where the mother is either the head of the household or the spouse of the head of the household and works in an occupation with at least 500 workers in the full sample. Birth quarter is based on *actual* birth quarter. Occupation classification is provided by the two-digit occupation codes from the census. The omitted occupational category is Arts, Design, Entertainment, Sports, and Media, as this occupation has Q2 + Q3 = 0.500(0.500). *F* tests for occupation report test statistics for the joint significance of the dummies and *F* test of age variables refers to the test statistic on the test that the coefficients on mother's age and age squared are jointly equal to zero. Critical values are 1.587 and 2.996 for occupational and age tests respectively. The Leamer critical value for the *t* statistic is 3.403. Heteroskedasticity robust standard errors are reported in parentheses. [a]Significance based on the Leamer criterion at 5%.

if we take into account that women on average take several (about 6) months to get pregnant after they stop contracepting. Indeed, birth seasonality has been found to be consistent with the seasonality at which women stop contracepting (Rodgers & Udry, 1988) but not with marriage seasonality timing (Lam, Miron, & Riley, 1994), which excludes honeymoon effects.

4 | WILLINGNESS TO PAY FOR SEASON OF BIRTH

4.1 | Measuring willingness to pay for season of birth

If there is a demand for season of birth, there must be a willingness to pay (WTP) for it—that is, a maximum amount of money an individual would be prepared to pay for having a baby born in a particular season. We estimate the WTP for season of birth using a discrete-choice experiment (DCE) approach, which is a variant of conjoint analysis (CA). This method attempts to explain and predict consumers' behavior on the basis of their preferences for the attributes of a good (Lancaster, 1966). CA methods are particularly useful for quantifying preferences for nonmarket goods, and have been applied successfully to measure preferences for a diverse range of health applications (Bridges et al., 2011). We can think of season of birth as one of the attributes associated with a birth, so that the DCE approach offers a natural procedure to measure the value of season of birth.

Before starting a DCE, the attributes characterizing the alternatives/scenarios need to be defined. In the case of a birth, we use the following attributes: season of birth, out-of-pocket expenses, gender, and birth weight or day of birth (randomly allocated to two groups of respondents). In the case of season of birth and gender, the levels are straightforward, namely [winter, spring, summer, fall] for the former, and [girl, boy] for the latter. The chosen values for out-of-pocket expenses (in USD) and birth weight were [250, 750, 1000, 2000, 3000, 4000, 5000, 6000, 7500, 10000] and [5 lb 8 oz, 5 lb 13 oz, 6 lb 3 oz, 6 lb 8 oz, 6 lb 13 oz, 7 lb 3 oz, 7 lb 8 oz, 7 lb 13 oz, 8 lb 3 oz, 8 lb 8 oz, 8 lb 13 oz], respectively. Finally, for day of birth, we defined the values as [weekday, weekend]. As noted by Ryan and Farrar (2000), the levels must be plausible and actionable, then encouraging the respondents to take the exercise seriously. Following Bridges et al. (2011), in defining the values for birth weight and out-of-pocket expenses, we avoid the use of extreme values that may cause a grounding effect, and, to avoid the use of heuristics by the respondents, we reduce the complexity of the task by providing a limited number of attributes over which choices must be made.

We use a main-effects design, which is orthogonal (all attribute levels vary independently) and balanced (each level of an attribute occurs the same number of times). In particular, the attributes are combined to form various (hypothetical) birth scenarios, all about a hospital birth of the first child with *no* complications.[20] By noting that the birth has no complications, we avoid associating a higher cost with complications. Every birth is therefore characterized by a vector of four parameter values, each randomly assigned to each scenario, and the order of the four characteristics is randomized across respondents. Respondents are asked sequentially whether they prefer Scenario 1 or Scenario 2, facing two birth scenarios in each round and playing for seven rounds, so that a DCE amounts to tracing out an indifference curve in the attribute space.[21] The screen shot of a round with a choice between two scenarios is presented in the Supporting Information Appendix as Figure A6.

4.2 | Estimating willingness to pay for season of birth

We present the theory behind the estimation of average marginal WTP using a discrete-choice experiment in the Supporting Information Appendix borrowing from Zweifel, Breyer, and Kifmann (2009, p. 60). Supporting Information Table A18 displays the descriptive statistics on the characteristics reported by our 3,661 valid Amazon Mechanical Turk respondents: these are black, white, Asian/Pacific Islander or Native American/American Indian, have an IP address located inside of the USA at the time of the survey, did not fail a consistency check in survey questions, and completed the survey in more than 2 minutes. 53% of respondents are women; on average, respondents are 36.7 years old; 8% of them are black; 84% are white; 6% are Hispanic; 47% are married; 89% of them have at least some college; 74% are employed; their average family income is about 60,000 USD; 11% work in “education, library, and training” occupations; 50% of them are parents; and, on average, they report having one child. According to Figure A7, the geographical coverage of our Amazon Mechanical Turk survey, map (a), broadly reflects the distribution of the US population recorded by the Census Bureau, map (b). Table A19 provides a comparison of our sample characteristics in M-Turk versus NVSS and ACS.[22]

In Table 4 we report the findings from our discrete-choice experiments.[23] Each column reports the average marginal effects corresponding to a logit regression where the dependent variable is to choose (or not) a given birth scenario based on the randomly assigned attributes of the birth. In column (1) we present the results for the full sample: Respondents are about 4 pp more likely to choose a birth scenario for their first birth if that scenario happens in spring. Moreover, for each additional 1,000 USD of out-of-pocket expenses they are 7 pp less likely to choose a birth scenario. The finding on the cost variable is consistent with our a priori expectation: The larger the costs of the birth scenario, the less likely it is that such a birth scenario is chosen. Our estimate of the WTP for their first birth occurring in spring, which can be obtained as the negative of the ratio of the (average) marginal effect of spring divided by the (average) marginal effect on out-of-pocket expenses (multiplied by 1,000), is about 620 USD, which is statistically significant even based on the demanding Leamer criterion. Allowing for preference heterogeneity by means of a mixed logit (Table A21 in the Supporting Information Appendix) does not affect our estimated average WTP for a spring birth (between 89% and 100% of our respondents positively value a spring birth).

In columns (2)–(4) we focus on married mothers aged 20–45. We find that among this group (column (2)) the average WTP is larger (877 USD). In columns (3) and (4), we investigate heterogeneity along number of children, and uncover that the average WTP is driven by married mothers aged 20–45 with two or more children (1,100 USD). In the final column,

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[20] Specifically, we instruct respondents:

> Imagine you and your partner are planning to have a baby or, if you have children already, think back to the time before the birth of your first child. You will have hopes and fears for how the birth will go.
>
> On the next screens we will show you pairs of possible birth scenarios, all about hospital births with no complications. The birth scenarios will differ in some respects/features.
>
> Please indicate on each screen which of the two scenarios you would prefer to happen for your child's birth (or if you already have children, which scenario you would have preferred to have happened for the birth of your first child).

[21] The assumptions embedded in the behavioral model underlying these choices are (i) the existence of a representative consumer (which can be relaxed using a mixed-logit), and (ii) the functional form of the utility function—typically linear (this can be relaxed to allow for a quadratic functional form, though is still restrictive).

[22] In our main specification we always use the unweighted MTurk sample; however, as an alternative we follow Francis-Tan and Mialon (2015) in reweighting the sample so that results are representative of the US population. Weighted results are reported in Table A20 in the Supporting Information Appendix.

[23] Respondents face two scenarios in each round, and play for seven rounds, which corresponds to 51,254 participant–scenario–round observations. The full sample regression is run adding indicators for missing birth weight (BW) and day of birth (DoB), since half of the respondents were randomly shown birth weight and the other half were shown day of birth as one of the attributes. In the end, we use BW = BW if available and BW = 0 if missing, and DoB = DoB if available and DoB = 0 if missing. In each case BW and DoB enter the regression categorically, and as such assigning a value of 0 is an arbitrary decision which has no impact on other estimated coefficients.

TABLE 4 Birth characteristics and willingness to pay for season of birth

	Full sample	Married mothers 20–45			Intended childless
	(1)	(2)	(3)	(4)	(5)
	All	All	1 child	≥2 children	20–45
Spring	0.042[a]	0.062[a]	0.020	0.080[a]	0.032
	[0.006]	[0.013]	[0.024]	[0.015]	[0.013]
Summer	0.020[a]	0.012	−0.005	0.018	0.010
	[0.006]	[0.013]	[0.023]	[0.015]	[0.012]
Fall	0.029[a]	0.038	0.015	0.047	0.014
	[0.006]	[0.013]	[0.025]	[0.015]	[0.012]
Cost (in 1000s)	−0.068[a]	-0.070[a]	−0.063[a]	−0.073[a]	−0.070[a]
	[0.001]	[0.001]	[0.003]	[0.001]	[0.001]
Girl	−0.006	0.011	−0.015	0.023	0.008
	[0.005]	[0.011]	[0.023]	[0.012]	[0.011]
5 lb 13 oz	0.014	0.013	0.014	0.010	0.029
	[0.014]	[0.032]	[0.071]	[0.036]	[0.030]
6 lb 3 oz	0.118[a]	0.131[a]	0.077	0.149[a]	0.121[a]
	[0.014]	[0.031]	[0.070]	[0.035]	[0.028]
6 lb 8 oz	0.144[a]	0.157[a]	0.084	0.186[a]	0.136[a]
	[0.014]	[0.033]	[0.059]	[0.040]	[0.029]
6 lb 13 oz	0.125[a]	0.163[a]	0.134	0.173[a]	0.115[a]
	[0.014]	[0.033]	[0.065]	[0.038]	[0.029]
7 lb 3 oz	0.181[a]	0.199[a]	0.158	0.210[a]	0.153[a]
	[0.015]	[0.031]	[0.061]	[0.036]	[0.031]
7 lb 8 oz	0.184[a]	0.166[a]	0.143	0.175[a]	0.161[a]
	[0.015]	[0.034]	[0.068]	[0.039]	[0.031]
7 lb 13 oz	0.151[a]	0.132[a]	0.070	0.154[a]	0.139[a]
	[0.014]	[0.032]	[0.068]	[0.036]	[0.029]
8 lb 3 oz	0.167[a]	0.233[a]	0.243[a]	0.225[a]	0.117[a]
	[0.015]	[0.034]	[0.073]	[0.039]	[0.031]
8 lb 8 oz	0.147[a]	0.180[a]	0.113	0.200[a]	0.147[a]
	[0.015]	[0.033]	[0.066]	[0.039]	[0.031]
8 lb 13 oz	0.146[a]	0.147[a]	0.062	0.173[a]	0.161[a]
	[0.014]	[0.033]	[0.070]	[0.038]	[0.030]
Weekend day	0.007	0.011	0.015	0.010	0.016
	[0.006]	[0.012]	[0.022]	[0.015]	[0.012]
WTP for spring (USD)	620.1	877.4	320.8	1098.3	454.8
95% CI	[337.1; 903.0]	[276.2; 1478.5]	[−910.2; 1551.8]	[412.4; 1784.3]	[−145.6; 1055.3]
Observations	51,254	10,304	3,038	7,266	11,060
Number of respondents	3,661	736	217	519	790

Note. Each estimation sample consists of US-based respondents to a Mechanical Turk survey with waves completed in September 2016 and May 2018. Any subsets of this sample are listed in column headings. Average marginal effects from a logit regression are displayed. All columns include option order fixed effects and round fixed effects, plus an indicator for the survey wave (2016 or 2018). The sample in each column is indicated in column headings. Standard errors are clustered by respondent. Willingness to pay and its 95% confidence interval are estimated based on the ratio of costs to the probability of choosing a spring birth. The 95% confidence interval is calculated using the delta method for the (nonlinear) ratio, with confidence levels based on Leamer values. [a]Significance based on Leamer criterion at 5%.

we focus on the group of individuals whom we define intended childless (they do not have children and are not planning to have children). The average WTP for this group is much smaller (455 USD) and not statistically different from zero.[24] Quite remarkably though, the effect of out-of-pocket expenses is essentially the same across all groups.

Is 877 USD a sizable magnitude? To answer this question we have calculated the value of a birth by adding the valuation of each characteristic in our regression. As all our valuations are relative (e.g., willingness to pay for spring compared

[24]The average WTP among those with one child is statistically different from that of those with two or more children at the 10% significance level, while the average WTP among those with one child is not statistically different from that of those intended childless. These results also hold when conditioning on maternal education and income, suggesting that this is unlikely to be simply proxying for systematic differences between these two groups.

with winter), all of these valuations must be taken as with respect to a baseline category, which in our case is a male, born in winter, during the week, and with the minimum birth weight in the range provided (i.e., 5 lb 8 oz, or 2,500 g). We made all these computations for the set of values in our discrete-choice experiments, obtaining that the largest relative estimate is that of the willingness to pay for a girl, born in spring, during the weekend, and with a birth weight of 7 lb 8 oz: 3,354.644 USD. In terms of birth weight, our estimates reveal that the value of a spring birth is equivalent to 560 g in the normal range—quite a sizable magnitude.

Does WTP for a spring birth explain actual spring births? To answer this question we first estimate the marginal WTP for spring births using a mixed logit for each married mother aged 20–45 (based on the results from Table A21). We then predict the estimated marginal WTP for spring births using maternal characteristics: age, age squared, an indicator for having a college education (or above), and race and ethnicity indicators in the M-Turk data. Assuming transportability from M-Turk to birth certificate data, we use the estimated coefficients on maternal characteristics to predict the marginal WTP for each married mother aged 20–45 in the birth certificate data. We then investigate the relationship between predicted marginal WTP and spring births in the birth certificate data, controlling or not for child characteristics (gender, day of birth, and birth weight). We find that a 1,000 USD increase in the predicted marginal WTP for a spring birth is associated with an increase in the actual probability of giving birth in spring by about 60%, or 15 pp (see Table A22 for details). This finding provides suggestive evidence that experimentally elicited behaviors using M-Turk samples do reflect actual choices observed.

5 | CONCLUSIONS

We study the determinants of season of birth for married women aged 20-45 in the USA, using birth certificate and Census data. We document that the probability of having a baby in spring is significantly related to mother's age, education, race, ethnicity, smoking status during pregnancy, receiving WIC food benefits during pregnancy, prepregnancy obesity, and the mother working in “education, training, and library” occupations, whereas the probability of having a baby in summer is not related to any of these observable characteristics, other than race and ethnicity. All our findings are muted among unmarried women with no paternity acknowledgment of their child. We also elicit the willingness to pay for season of birth through discrete-choice experiments implemented on the Amazon Mechanical Turk platform. Among married women aged 20–45, we estimate the average willingness to pay (WTP) for a spring birth to be 877 USD or 560 g of birth weight in the normal range. The average WTP seems to be driven by mothers aged 20–45 with two or more children.

Our analysis combining observational administrative data with experimental online survey data provides evidence that season of birth is a choice variable for those who plan fertility, and does not mechanically follow biological constraints for all women. While earlier work, particularly that of Buckles and Hungerman (2013), has documented that birth timing depends on the choices made by parents, our analysis elicits for the first time a direct measure of preferences in birth timing. This demand for season of birth dwarfs demand for particular days within the week or the gender of the child, and responds to the information available to parents. Moreover, the experimentally elicited demand for season of birth helps to rationalize observed fertility behaviors in the US population.

Our study may help policymakers to better assess and design policies targeting job flexibility, parenthood, and child health and development; this is particularly important in the USA, where maternity leave provisions are very limited. If prospective mothers generally share a common preference for spring births, which is a reasonable assumption taking into account that 100% of our married mothers aged 20–45 in M-Turk positively value a spring birth,[25] but only those working in occupations with favorable conditions, or whose partners can economically support maternal leave, could fulfill these preferences, a generous maternal leave policy would improve the ability that individuals have to optimally target births within the year.[26] This would allow those with less flexibility to shift their births to their desired season, changing observed

[25]This proportion is estimated based on mixed-logit coefficient estimates of both the mean and standard deviation of the impact of spring birth on a preferred birth profile, assuming normality in preference heterogeneity. Specifically, this is calculated as $100 \times \Phi\left(\frac{-\hat{\beta}^{\mu}_{\text{spring}}}{\hat{\beta}^{\sigma}_{\text{spring}}}\right)$, where Φ is the normal CDF, and $\hat{\beta}^{\mu}_{\text{spring}}$ and $\hat{\beta}^{\sigma}_{\text{spring}}$ are the estimated mean and standard deviation of the impact of spring birth on a given birth choice. See Hole (2007) for additional details.

[26]With a maternity leave in the USA, the number of families who would likely change birth timing to their “optimal” seasons is unlikely to be trivial. A back-of-the-envelope calculation based upon the data and results of this paper allows us to consider what proportion of families would shift births to Quarter 2 if a paid family leave policy (PFLP) was in place. Specifically, consider that women working in education, library, and training occupations are 3.4% more likely to have a spring birth than other women (see Figure 1b), to take advantage of a long summer leave following their birth. We can then ask what would happen if women in other occupations had a similar shift to optimal seasons following the introduction of a PFLP, which allowed for a leave similar in nature to “teachers'” summer break. From Supporting Information Table A14, 86.2% of women work in noneducation, library,

birth timing within the country across the year, and, not least of all, increasing child health at the population level (Currie & Schwandt, 2013).

Of course, the costs of a comprehensive paid family leave policy would be considerable. A recent AEI-Brookings working group report estimates that offering 8 weeks leave with a 70% wage replacement would cost 3.5–11.8 billion USD, with estimated average benefits per recipient of 1,850–2,500 USD.[27] It is interesting to note that, while these average costs exceed our estimated WTP for achieving desired season of birth in the paper, they are of a similar order of magnitude. Given the mixed evidence on the case for paid family leave (see Olivetti & Petrongolo, 2017, for a review) it is important to note that achieving desired birth timing may be an overlooked benefit of such a policy.

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and training occupations, and from Figure 1(b) 3.4% of these would shift their birth season if they behaved similarly to Education, Library and Training workers once family leave was introduced. This very rough calculation suggests that as many of 2.9% of births may shift season ($0.862 \times 0.034 = 0.029$).
[27]See the report by Gitis, Glynn, and Hayes (2018).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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