On the Value of Birth Weight*

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Abstract

A large body of evidence documents the educational and labor market returns to birth weight, which are reflected in investments in large social safety net programs targeting birth weight and early life health. However, there is no direct evidence on the *private* valuation of birth weight. In this paper we estimate the willingness to pay (WTP) for birth weight in the US, using a series of discrete choice experiments. Within the normal birth weight range (2,500 g - 4,000 g), we find that individuals are, on average, willing to pay $1.47 (95% CI: [$1.24, $1.70]) for each additional gram of birth weight when the value of birth weight is estimated linearly, or $2.40 (95% CI: [$2.03, $2.77]) when the value of birth weight is estimated non-parametrically.

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1 Introduction

The weight of a newborn is a well-known measure of the initial endowment or stock of human capital early in life (Almond and Currie, 2011; Almond, Currie and Duque, 2018). The importance of the fetal period as a predictor of health throughout the life course has been recognized in a series of influential papers by Barker and coauthors on the fetal origins of disease (Barker et al., 1989; Barker, 1990, 1995), with considerable and ever-growing evidence that insults to fetal health have enduring and significant costs throughout life (Case, Fertig and Paxson, 2005; Almond, 2006; Currie and Moretti, 2007; Black, Devereux and Salvanes, 2007; Almond, Edlund and Palme, 2009). These findings justify sizeable welfare programs targeted at babies with poor endowments early in life, such as those focusing on low birth weight infants (Almond, Chay and Lee, 2005; Bharadwaj, Løken and Neilson, 2013) and pre-natal nutrition programs, such as the Special Supplemental Nutrition Program for Women Infants and Children (WIC).

Despite a large body of evidence on the importance of birth weight and considerable public investment, little is known regarding the private valuation of this birth outcome, or other newborn measures. Knowing the value which people place on birth weight and other birth characteristics is of public concern and a fundamental policy issue, in particular as a key ingredient to policies focused on parental behavior *prior* to and *during* gestation. To the degree that a wide range of (costly) parental behaviors can positively impact birth weight (Rosenzweig and Schultz, 1983; Sexton and Hebel, 1984; Chevalier and O'Sullivan, 2007), the perceived importance of birth weight to parents may have significant effects on these behaviors.

In this paper we estimate the importance of birth weight to individuals, as measured by their Willingness to Pay (WTP) for birth weight. In order to do so, we conducted a series of discrete choice experiments on Amazon Mechanical Turk, an online labor market platform. This is increasingly used in social science research (Kuziemko et al., 2015; Jordan et al., 2016) and, in particular, a recent study has relied on this platform to estimate the value of life before and after birth (Jamison, 2016). We conducted these experiments with approximately 2,000 respondents, half of them interviewed in 2016, and half of them in 2018. Respondents were asked to consider seven pairs of birth scenarios sequentially, amounting to around 28,000 different birth scenarios with a number of different characteristics. These characteristics were each orthogonally varied both within and between experimental subjects. Specifically, we performed conjoint analysis, a method first described by Lancaster (1966).

These experiments allow respondents to reveal their preferences (or lack thereof) over a range of birth characteristics. In particular, we randomize a baby's birth weight, monetary costs of birth, gender, and birth timing. Birth weight was randomized within the normal range of 2,500 to 4,000 grams. We restrict our analysis to the "normal" range for two reasons. First, not only do

continuous measures of birth weight have greater explanatory power for a larger range of variables than a low birth weight (LBW, or weights less than 2,500 grams) indicator (Black, Devereux and Salvanes, 2007), but recent evidence also suggests that marginal increases in birth weight within the normal weight range are particularly important for well-being. Royer (2009) suggests that given this fact, babies born in the normal range of weights should receive *more* research attention.[1] Indeed, Maruyama and Heinesen (2020) show that health effects of low birth weight exist also in the normal range. Second, from a purely practical standpoint, we focus on the normal range of birth weights to avoid priming effects (i.e., respondents linking low birth weight with other health conditions or complications at birth), thus confounding our estimates for the WTP of birth weight alone.

We find that a baby weighing 3,400 grams (7lbs, 8oz) is 18 percentage points (pp) more likely to be preferred than one weighing 2,500 grams (5lbs, 8oz). We estimate that over the normal range of birth weights, experimental participants would be willing to pay on average \$1.47 (95% CI: [\$1.24, \$1.70]) for each additional gram of weight when the value of birth weight is estimated linearly, or \$2.40 (95% CI: [\$2.03, \$2.77]) when the value of birth weight is estimated non-parametrically.

Our experimental estimates are consistent with studies showing that individuals make fertility-related decisions based on monetary costs and non-pecuniary birth characteristics. Dickert-Conlin and Chandra (1999) and LaLumia, Sallee and Turner (2015) report that in the US parents may move expected January births backwards to December to gain tax benefits, and Schulkind and Shapiro (2014) clearly show that parents are willing to anticipate the births of their children to gain tax benefits despite impacts of this on their child's birth outcomes. They find that a \$1,000 increase in tax benefits translates into an approximately 0.37 percentage point increase in the probability of a December birth. Moreover, they show that shifts in birth timing owing to the additional \$1,000 in tax benefits causes between a 0.07% and 0.19% decrease in average birth weight, or between 2.41 and 6.37 grams. Combining these two findings, we obtain an estimated WTP for birth weight of \$1.17-\$3.09 per gram, a range of non-experimental magnitudes which matches with our experimental estimates.

In what follows, we describe the Mechanical Turk data and experimental set-up in section 2 and the methodology for estimating WTP in section 3. In section 4 we present our experimental estimates of the WTP for birth weight. In section 5 we assess the validity of our experimental findings, and place them in broader context. In section 6 we check the robustness of our findings to preference heterogeneity. Section 7 concludes.

[1] In full, Royer (2009) reports (p. 52):

> "I find that the effects of birth weight on long-run outcomes are nonlinear and for educational attainment, in particular, are largest above 2,500 grams, the cutoff for defining low birth weight. These findings suggest that babies with birth weights outside the lower tail of the distribution (i.e., outside the range of low birth weight) should receive more attention."

2 Data Description

We collected data on preferences over birth characteristics by running discrete choice experiments on Amazon's Mechanical Turk (MTurk) online platform. This platform is a market place which provides access to a pool of US MTurk workers who are paid per completed HIT (Human Intelligence Task). We posted a HIT request to recruit respondents to complete a series of discrete choice experiments (described further below) as well as a series of demographic questions. These demographic questions were asked *after* the completion of the experiments to avoid any framing or experimenter demand effects (Zizzo, 2010), and the survey was advertised as a general demographic survey. MTurk respondents have been documented to have desirable characteristics, and be more similar to the US population than other frequently-used subject pools such as college student samples (Berinsky, Huber and Lenz, 2012). While MTurk samples are increasingly used in social science research, the pool of subjects consists of individuals who sign up to participate in MTurk tasks, and so is self-selected. Nonehtheless, MTurk is a valuable research tool to collect data and use conjoint analysis in the context of research in health (Mortensen and Hughes, 2018). In their review Mortensen and Hughes (2018) highlighted several strengths of MTurk, including its reliability and the high quality of the information provided by the participants, with comparability to responses in high quality data samples. In addition, MTurk allows researchers to collect large national pools of data, including quantitative and qualitative data about patients' knowledge and experience with events such as miscarriage (Bardos et al., 2016), while also documenting comparability among responses in MTurk samples, and university-wide communities (Wu et al., 2017).

We published two HITs containing an identical experiment at different time periods. The first of these was published on a Monday in September 2016, and the second of these was published on a Monday in May 2018[2], requesting the completion of a short survey. In the second HIT, we prevented any previous respondents from completing the survey to avoid priming effects. Workers were paid \$1.10 for a 6 minute experimental survey (average length) in the first wave, resulting in an effective hourly pay rate of approximately \$11. This payment was increased to \$1.20 to correct for inflation in the second wave. The survey needed to be completed in order to be able to receive payment, and it was impossible to move forward if the question on the screen was not answered. We required that respondents must be from the United States,[3] and in order to maximize the likelihood that workers were based in the US at the time of completing the survey, this was launched at 9:00 AM East Coast Time in both cases. In both cases, by approximately 2:00 PM of the same day 1,002 and 1,003 valid responses were collected. We also required that workers had completed at least 100 tasks on MTurk in the past, and had achieved an approval rating of greater than 95% on these tasks. These

[2]We were interested in examining robustness over time and in different seasons of the year. Results from only the first HIT are presented in a previous version of this working paper (Clarke, Oreffice and Quintana-Domeque, 2017), and are qualitatively identical to those we document below from the larger two-wave experiment.

[3]Workers on Mechanical Turk are required to have a US Social Security Number.

restrictions are common in Mechanical Turk research (Berinsky, Huber and Lenz, 2012; Francis-Tan and Mialon, 2015). Of the 2,005 valid responses completed, we removed a small number based on a set of pre-defined consistency checks. These were: (a) workers whose geographical IP address placed them outside of the US at the time of survey (72 respondents, or 3.6%), any respondents who failed a consistency check where a question was repeated at the beginning and end of the demographic portion of the survey (26 respondents), and any respondents completing the entire exercise in under 2 minutes (16 respondents). The final sample consists of 1,894 respondents.[4]

Summary statistics of the respondents are provided in Table 1. Slightly more than half of all respondents are female (53%), and the average age of our respondents is 36.5 (with a standard deviation of 11.7 years); 82% are white and 8% are Hispanic. Approximately half of the respondents are parents (50%), and of those who are non-parents, 47% intend to have children or are already pregnant (implying that 27% of respondents are neither parents, nor intend to become so). In total, 45% of the respondents are married, 73% are employed and 89% have at least some college.

The geographic location of these respondents within the US (based on their IP address) is provided in the online appendix Figure A1. The geographic coverage is broadly representative of the US population. In the online appendix Table A1 we compare our MTurk respondent coverage with the US population from 2015 (United States Census Bureau, 2015). In general, we see that our MTurk sample lines up well with the national population at the state level, however there are a number of exceptions, such as the lower number of respondents from California, most likely reflecting the earlier time zone on the West Coast.

In the online appendix Table A2 and Figure A2 we compare the observable (average) characteristics of our MTurk sample to those of the US population based on the 2015 American Community Survey (ACS). In each case in Table A2, we present descriptive statistics from each sample, as well as a formal test of equality of means. We observe that the MTurk sample is on average younger and consists of a higher proportion of white and parent respondents. MTurk respondents are more likely to be women, more educated but with lower income. In Figure A2 we compare the distribution of family income in the MTurk vs. the ACS: our MTurk sample has fewer individuals in the bins above $80,000 and more individuals in virtually all the bins below $80,000.

3 Methodology

In order to estimate the perceived importance of birth weight in terms of willingness to pay, we run discrete choice experiments. A discrete choice experiment (DCE) is a type of Conjoint Analysis (CA): An experiment in which respondents are asked to choose their preferred option from

[4]The categories of removed cases are not mutually exclusive.

a set when a number of attributes are varied simultaneously. CA was borne from early work in consumer theory in which tastes for goods owe to the collection of their characteristics (Lancaster, 1966). In the past, CA has been used to measure preferences over medical care in a variety of contexts, including the valuation of waiting times (Propper, 1990, 1995), alternative miscarriage treatment options (Ryan and Hughes, 1997), asthma medications (King et al., 2007), or depression management (Wittink et al., 2010). In other settings, theoretical choices in conjoint analysis have been documented to agree with actual choice behavior in the real world, and outperform vignette experiments (Hainmueller, Hangartner and Yamamoto, 2015).

Our birth choice experiments consist of asking respondents to consider a series of paired birth scenarios, while focusing on four attributes of each birth scenario. We use a main-effects, orthogonal (all attribute levels vary independently) and balanced (each level of an attribute occurs the same number of times) experimental design. In the experiment the attributes are combined to form various (hypothetical) birth scenarios, all about a hospital birth of the first child with no complications. The attributes considered are the baby's weight at birth (5lbs, 8oz; 5lbs, 13oz; 6lbs, 3oz; 6lbs, 8oz; 6lbs, 13oz; 7lbs, 3oz; 7lbs, 8oz; 7lbs, 13oz; 8lbs, 3oz; 8lbs, 8oz; or 8lbs, 13oz), the out of pocket expenses associated with the birth ($250; $750; $1,000; $2,000; $3,000; $4,000; $5,000; $6,000; $7,500; or $10,000), the sex of the child (Boy or Girl), and the season in which the baby is born (Winter, Spring, Summer or Fall). The latter options are used in order to avoid priming respondents into thinking that we are interested in birth weight. As these attributes are all orthogonally varied, the effect of each characteristic on the likelihood that a particular birth is chosen is separately identified (Marshall et al., 2010).

Each respondent was asked to consider seven pairs of birth scenarios in an iterative fashion. In order to move forward in the experiment a choice must be made for each pair, and once the choice has been made the respondent may not go back and revise their choice. In each case the two pairs were displayed side-by-side on a single screen, and respondents were asked to indicate which was their preferred birth scenario. As well as randomizing the level of each attribute on each profile, the order of the attributes was randomized, however to reduce the cognitive load to respondents the ordering of attributes was only randomized once, and then fixed across the seven pairings that the respondent ranked. The DCE's framing and the explanation of the attributes shown to respondents are displayed in the online appendix Figures A3 and A4. In Figure A5 we display an example of a pair of birth scenarios as presented to respondents.

The levels of attributes were chosen to represent plausible values from the US population (Ryan and Farrar, 2000), and extreme values were avoided to prevent the likelihood of "grounding effects" (or corner solutions), following Bridges et al. (2011). In order to minimize the likelihood that respondents would employ simple heuristics in answers, we limited the number of attributes (four) which need be considered. As discussed in Bridges et al. (2011), we observe in experimental responses

that such heuristics are not employed given response sensitivity to all dimensions studied. Birth weights were always presented in pounds and ounces, as this experiment was run with a US-sample. As well as indicating that all births were *complication-free*, only birth weights *within* the normal range of 2,500–4,000 grams were included (11 evenly-spaced weights were defined in this range). This range includes the vast majority of all births in the US.[5] From our reading of the US literature on out-of-pocket medical expenses, the US insurance system, and hospital bills in the US for the delivery of a baby, the value range from $250 to $10,000 seemed a plausible range for 2016 and 2018. Recent evidence from the United States (Moniz et al., 2020) suggests that for individuals with employer based insurance (around 50% of deliveries in the US), the average out of pocket costs for a birth were $4,569 in 2015. This is quite close to the mid-point in the values provided in the experiment. Among women not covered by employer based insurance, the large majority of births (90%) are covered by Medicaid, and so likely have lower copayments. In the DCEs it is stated that the birth scenarios refer to a "hospital birth of first child with no complications" so that the out-of-pocket expenses are associated to a healthy hospital delivery and represent the monetary valuation of the attribute "birth weight" in our DCEs. An opt-out option was not included in any of the discrete choices. This has been suggested to have desired properties such as avoiding non-random opt-out of all questions (Bekker-Grob, Ryan and Gerard, 2012; Veldwijk et al., 2014).

We are interested in estimating two quantities. Firstly, we would like to estimate, *ceteris paribus*, the likelihood that a birth scenario is chosen given that a particular birth weight is observed (compared with an omitted base category). Secondly, we would like to estimate the willingness to pay for birth weight, by combining the information from both variations in birth weight and variations in out-of-pocket costs.

Consider a sample of $i \in \{1, \ldots, N\}$ individuals, each of whom considers K choice tasks in which they must decide between J options (profiles, or in our case, birth scenarios). Each profile contains L attributes, where each particular attribute l consists of discrete levels of the variable. In the case of the DCE described above, we have $N = 1,894$ respondents, $K = 7$ choice tasks per respondent, $J = 2$ profiles per task, and $L = 4$ attributes.[6] We follow Hainmueller, Hopkins and Yamamoto (2013) in defining a treatment vector T_{ijk}. This treatment vector has L cells, and summarizes for individual i, at choice task k, for profile j, the full set of attributes observed. Each particular attribute T_{ijkl} is randomly assigned from among all the levels of l, the assignment of which is orthogonal to all other attributes the respondent sees. Using the potential outcomes framework, we define a binary variable $Y_{ijk}(\bar{\mathbf{t}})$ which takes the value 1 if respondent i would choose profile j on choice set k if faced with the set of attributes $\bar{\mathbf{t}}$, or 0 if the profile would not be chosen.

[5] According to full vital statistics of 2013 from the National Vital Statistics System (see Figure A6 in the online appendix), 8.02% of births were low birth weight (< 2,500 grams), and 7.89% were large for gestational age at birth (> 4,000 grams).

[6] These four attributes have 2, 10, 11 and 4 levels respectively for sex, out of pocket costs, birth weight and season of birth.

Hainmueller, Hopkins and Yamamoto (2013) call this first quantity the Average Marginal Component Effect (AMCE) and demonstrate that under reasonably weak assumptions,[7] it can be recovered using a non-parametric sub-classification estimator, conditional regression, or a simple difference in means. The logic of the AMCE is to capture the change in the likelihood that a given profile would be chosen if the l^{th} component were changed from t_0 to t_1, or in our case, a change in birth weight.[8]

Under the controlled randomization in conjoint analysis, Holland (1986)'s fundamental problem of causal inference is resolved by construction, as on average there will be no correlation between observing the particular level of an attribute and individual characteristics. Treatment units are thus those who observe a particular t_1, while those who do not act as controls. In practice, to estimate the change in the likelihood that a birth scenario is chosen given a change in birth weight (or any other attribute), we estimate the following two equations:

$$Pr(Y_{ijk} = 1) = \Lambda \left(\alpha + \beta Costs_{ijk} + \gamma BW_{ijk} + \sum_{r=2}^{4} \delta_r SOB_{ijk,r} + \kappa Girl_{ijk} + \mu_j + \phi_k \right) \tag{1}$$

and

$$Pr(Y_{ijk} = 1) = \Lambda \left(\alpha + \beta Costs_{ijk} + \sum_{q=2}^{11} \gamma_q BW_{ijk,q} + \sum_{r=2}^{4} \delta_r SOB_{ijk,r} + \kappa Girl_{ijk} + \mu_j + \phi_k \right), \tag{2}$$

where $Y_{ijk} = 1$ if the birth scenario j is chosen, Λ is the *cdf* of the logistic distribution, $Costs_{ijk}$ denotes the out of pocket expenses associated with the birth scenario j, BW_{ijk} is the birth weight associated with the birth scenario j, $BW_{ijk,q}$ is equal to 1 if the birth weight category of the birth scenario j is q, $SOB_{ijk,r}$ is equal to 1 if the season of birth category of the birth scenario j is r, $Girl_{ijk}$ is 1 if the gender of the baby of the birth scenario j is girl, and μ_j and ϕ_k are option-profile and choice-task order fixed effects, respectively. Standard errors are clustered at the level of the respondent to capture the (likely) positive correlations among choices based on attributes by a particular respondent.

We estimate equations (1) and (2) and report average marginal effects. We omit from equation (2) the lowest birth weight category as the baseline level, implying that all marginal effects of each birth weight should be interpreted as the marginal likelihood of choosing a birth scenario given birth weight q in place of the lowest birth weight (2,500 grams).

We then estimate the average willingness to pay for birth weight in two different ways: using

[7] These assumptions relate to randomization of attributes, and stability of respondent behavior regardless of the number of profiles that they have seen or the order of the attribute in the profile. This first assumption holds by construction in our experiment. A benefit of the set-up of the DCE is that even if order and round effects are not completely neutral, these can be flexibly captured using fixed effects in a regression.

[8] Formally, the AMCE is defined as (Hainmueller, Hopkins and Yamamoto, 2013):

$$E[Y_i(t_1, T_{ijk[-l]}, \mathbf{T}_{i[-j]k}) - Y_i(t_0, T_{ijk[-l]}, \mathbf{T}_{i[-j]k}) | (T_{ijk[-l]}, \mathbf{T}_{i[-j]k}) \in \tilde{\mathcal{T}}]$$

which can be quite easily calculated by integrating over all of the other attributes and levels except for t_1 (the treatment of interest) and t_0 (the baseline level for the attribute). These other attributes and levels are denoted as the set $\tilde{\mathcal{T}}$ here.

equations (1) and (2), respectively. From equation (1), the marginal effects on the likelihood of choosing a particular birth scenario given an increase in the particular attribute, conditional on all other attributes, are:

$$\frac{\partial Pr(Y_{ijk}=1)}{\partial Costs_{ijk}} = \beta\Lambda'(\cdot) \qquad \frac{\partial Pr(Y_{ijk}=1)}{\partial BW_{ijk}} = \gamma\Lambda'(\cdot),$$

where Λ' is the *pdf* of the logistic distribution. Given these marginal effects, the marginal rate of substitution (MRS) between birth weight BW and the price of a given birth (the out of pocket costs)—which measures the change in costs that a respondent would be willing to withstand for a marginal increase in birth weight—is given by:

$$MRS_{BW,Costs} = \frac{\frac{\partial Pr(Y_{ijk}=1)}{\partial BW_{ijk}}}{\frac{\partial Pr(Y_{ijk}=1)}{\partial Costs_{ijk}}} = \frac{\gamma}{\beta}.$$

Multiplying this quantity by minus 1 gives precisely the willingness to pay:

$$WTP_{BW}(1) = -\frac{\gamma}{\beta} = -\frac{\partial Cost_{ijk}}{\partial BW_{ijk}}.$$

Note that in the above calculation we take the negative so that costs are interpreted as the positive amount that must be paid rather than the negative change in financial resources. This WTP can also be derived quite straightforwardly from a model of the indirect utility function as described in Zweifel, Breyer and Kifmann (2009). In order to calculate the confidence interval associated with the WTP we use the *delta method*, which is both simple and shown to perform well under simulation (Hole, 2007*a*).

Finally, we also compute the average WTP based on equation (2) as:

$$WTP_{BW}(2) = -\frac{1}{\beta}\sum_{q=2}^{11}\omega_q\gamma_q,$$

where ω_q is the fraction of births with weight between $q-1$ and q in the birth data from National Vital Statistics System (NVSS) over the normal birth weight range so that $\sum_{q=2}^{11}\omega_q = 1$.[9] A 95% confidence interval for this second WTP measure is also constructed using the delta method.

[9] $q=1$ corresponds to 2,500 g, $q=2$ to 2,637g, $q=3$ to 2,807g , $q=4$ to 2,948g, $q=5$ to 3,090g, $q=6$ to 3,260g, $q=7$ to 3,402g, $q=8$ to 3,544g, $q=9$ to 3,714g, $q=10$ to 3,856g, and $q=11$ to 4,000g.

4 Experimental Results

4.1 Results for the Whole Sample

Figure 1 shows that the randomization worked as intended: it balanced observable characteristics across the range of experimental attributes. In examining 12 observable characteristics of respondents, an Omnibus F-test suggests no lack of balance at any conventional significance level in each case. Our main experimental results are presented in Figure 2. This figure displays point estimates of the likelihood of preferring a particular birth scenario given each characteristic, compared with an omitted base category for each characteristic. Along with each point estimate, the 95% confidence interval is plotted, clustering by respondent. While we present cost as a linear variable measured in 1,000s of dollars, in the online appendix Figure A7 the same results are presented with costs displayed as the same categorical measure observed by respondents.[10]

The top panel displays the likelihood of choosing a birth scenario given a particular birth weight, compared to being shown the minimum sample birth weight of 5lbs, 8oz (2,500 grams). In each case, higher birth weights are associated with a greater likelihood of choosing the corresponding birth scenario. The most preferred birth weight (based on point estimates) is 7lbs, 8oz (3,400 grams), which results in a birth scenario being approximately 18 pp more likely to be chosen than the omitted base category. The magnitudes of the estimates are large. With the exception of 5lbs, 13oz, all higher birth weights are at least 12 pp more likely to be chosen.

As discussed in section 3, we can combine estimates of average marginal component effects to generate estimates of the WTP for each characteristic. In Table 2, column 1, we assume a linear functional form for birth weight. By comparing the change in the likelihood of choosing a birth scenario based on an increase in birth weight with the change in likelihood due to an increase in costs, we estimate that the average WTP for an additional 1,000 grams in the full sample is \$1,470.3, or \$1.47 per gram (95% CI: [\$1.24, \$1.70]). As expected, we observe that all else equal, higher costs result in a birth scenario being less likely to be preferred. On average, for each additional \$1,000 in out of pocket expenses, the likelihood of choosing a birth scenario falls by 6.3 pp.[11]

When calculating the average WTP of birth weight as a single figure, this is based on a specification in which birth weight (and costs) enter the estimating equation linearly. However, as we observe in column 2 of Table 2, the relationship between birth weight and the likelihood of choosing a birth scenario is non-linear. In Figure 3 we document the WTP of all birth weight options, with respect to the minimum birth weight in the sample. We observe that the largest relative difference occurs at

[10] In the online appendix Figure A8 we document that results are largely unchanged if we work with the full sample of 2,005 respondents rather than the preferred sample of 1,894 respondents meeting inclusion criteria.

[11] In the online appendix Table A3 we follow Francis-Tan and Mialon (2015) and *re-weight* the sample so that it has a geographical distribution that is representative of the US population. We find quantitatively and qualitatively similar results.

3,400 grams (7lbs 8oz, compared with the omitted base of 2,500 grams). Using the non-parametric WTP estimates we obtain an average WTP of $2.40 per gram (95% CI: [$2.03, $2.77]).

It is also illustrative to compare WTP for birth weight to estimated WTP for other characteristics. Using point estimates from Table 2, we estimate a WTP for a girl (rather than boy) birth of only $47, and estimate a WTP for a spring (rather than winter) birth of $539. Note that this can also be cast in terms of trade-offs related to birth weight. On average in the experimental sample, we estimate a willingness to accept 32 fewer grams of birth weight to achieve a girl birth, and 370 fewer grams of birth weight to achieve a preferred season (spring) birth.

4.2 Results by Parental Status

The headline estimated effect for average WTP suggests a value of $1.47 per gram over the range examined (95% CI: [$1.24, $1.70]). This value is calculated using the entire sample of respondents. We briefly consider estimates for particular subgroups of interest, namely parents, non-parents, and non-parents who do and do not intend to have children. All these basic demographic characteristics were asked *after* the completion of the experiments.

Figure 4 displays outcomes of the discrete choice experiments for each group. Panels A and B split by parental status (parents versus non-parents), and then panels C and D further split non-parents by desired childbearing status (those who intend to have children or are already pregnant versus those who do not intend to have children). These figures reveal that parents are the most sensitive to changes in birth weight. Non-parents display a much flatter profile, and are consistently less likely to choose a birth scenario given a higher birth weight. When further splitting by those who intend to have children and those who do not, we observe that the profile for the former is comparable to that for parents, while those who do not intend are significantly less likely to choose a birth scenario based on an increase in weight. We examine these results, along with precise values for WTP, in Table 3.

Parents vs. non-parents. In columns 2 and 3 of Table 3 we estimate the linear specification for birth weight and costs for parents and all non-parents. We observe, firstly, that although both groups are similarly impacted by increases in costs (a birth scenario is 6.1 pp or 6.4 pp less likely to be chosen for each $1,000 increase in costs for parents and non-parents respectively), point estimates on birth weight are higher for parents than for non-parents. An increase in 1,000 grams of birth weight increases the likelihood that parents choose a profile by 9.8 pp, while only by 8.6 pp for non-parents. This is reflected in different average WTP values. The average WTP for a gram of birth weight among *parents* is $1.60, (95% CI: [$1.26, $1.94]), compared to $1.35 among non-parents, (95% CI: [$1.04, $1.67]). Perhaps unsurprisingly, across the board parents are more likely than

non-parents to be swayed by changes in non-pecuniary attributes: For parents both birth weight and birth season are more important than for non-parents. We estimate a pooled specification where we interact a dummy for being a parent with birth weight in Appendix Table A4. This allows us to estimate the WTP differential between parents and non-parents and its 95% confidence interval. While the average WTP differential is notable—at \$186 for an additional 1,000g—it is not statistically distinguishable from zero at the 5% significance level (95% CI: $[-\$258, \$631]$). However, we reject the hypothesis that the average WTP among parents is less than or equal to that among non-parents in favor of the alternative hypothesis that the former is *larger* than the latter at the 5% significance level (p-value=0.042) in a one-sided test.[12]

If parents are more educated, wealthier, and/or older, their estimated WTP could owe to these differences, and potentially be higher than that of non-parents due to greater availability of financial resources and a different information set than non-parents (e.g., they know what a normal birth weight is, and may even appreciate its return). Since parents are both wealthier and older than non-parents (see Table A5 in the online appendix), it is important to check that the WTP for birth weight does not change once we interact characteristics where they differ (namely, age and income). The comparison of columns (1) and (2) in Table A6 in the online appendix reveals two interesting findings: (a) accounting for interactions between birth weight and individual characteristics leads to very similar point (and interval) estimates and (b) the interactions between birth weight and individual characteristics appear to be unrelated to the probability of choosing a birth scenario.[13]

Parents vs. non-parents who intend to have children. Columns 4 and 5 of Table 3 display estimates for non-parents, separating by whether they intend to have children or do not intend to have children. If we compare figures for parents with those of non-parents who state that they *do* intend to have children, we see that the point estimate on birth weight is slightly higher among the former. As above, parents are 9.8 pp more likely to choose a birth scenario for each 1,000 grams increase in birth weight, while the same figure for non-parents who intend to have children is 9.2 pp. The average WTP of the non-parent planners is \$1.48 per gram (cf 1.60 for parents) with a 95% CI of \$1.01–\$1.94. Once again, if we refer to the online appendix Table A4 we see that the difference in average WTP is not statistically significant (column 3) at the 5% significance level. Moreover, we cannot reject the hypothesis that the average WTP among parents is less than or equal to that among non-parents who intend to have children against the alternative that the former is *larger* than the latter (p-value=0.194).[14]

[12]The p-value for this one-sided hypothesis test is obtained as 1 minus the proportion of times that the estimated WTP among parents exceeds that of non-parents, when WTP for each group is calculated 500 times in a bootstrap resampling procedure, clustering over respondents.

[13]For completeness, the online appendix Table A7 shows that allowing for heterogeneous valuations of birth weight by age, education and income does not affect our results in the full sample of respondents.

[14]Once again, after controlling for interactions between birth weight and individual characteristics (see Table A6), we obtain very similar point (and interval) estimates. In addition, the interactions between birth weight and individual characteristics appear to be unrelated to the probability of choosing a birth scenario among non-parents who intend

Non-Parents who intend to have children vs. non-parents who do not intend to have children. Finally, if we compare the two groups of non-parents, those who intend to have children and those who do not, we see a large average difference in the likelihood to choose a birth given an increase in birth weight. As above, non-parents who intend to have children are 9.2 pp more likely to choose a birth scenario for each 1,000 gram increase in birth weight, while non-parent non-planners are only 8.2 pp more likely. The average WTP for each group is $1.48 per gram for those who intend to have children versus only $1.25 per gram for those who do not intend to have children, or an 18% increase. We cannot formally reject the null hypothesis that the average WTP among non-parents who intend to have children is less than or equal to that among non-parents who do not intend to have children at the 10% significance level (p-value=0.317).[15]

While the point estimates suggest the existence of heterogeneity in WTP for birth weight among groups, from $1.25 per gram for individuals who intend to be childless to $1.60 per gram for parents, the confidence intervals are quite large, so that homogeneity in WTP across groups is indeed compatible with our findings. This is recognized in the formal tests of equality of coefficients presented in Table 3, both when comparing parents with non-parents, and parents with only that sub-group who intend to remain childless. It is important to note that, while this magnitude in the difference between parents and those who intend to be childless may appear small (at 35 cents per gram according to point estimates), this difference accounts for nearly 30% of the *total* estimated WTP among intended childless, or 22% among parents. As we discuss at more length in the next section (subsection 5.3), there is evidence that birth weight may be considerably undervalued by individuals given its importance as a precursor for labor market and other lifetime outcomes.

4.3 Results by Demographic Characteristics

Finally, in panels E-H of Figure 4 and in Table 4 we consider heterogeneity by both respondents' education, and by their family income level. Once again, while we observe considerable heterogeneity in point estimates, these are not sufficiently precisely estimated to allow us to reject tests of equality of WTP between groups. In columns 2 and 3 of Table 4 we observe around a 20 cent difference in WTP per gram of birth weight when comparing families with total incomes below $55,000 USD to those with incomes above this threshold. This difference is significantly larger among individuals with at least some college and those with no college education. In this case, point estimates, while very noisy, suggest that those *without* college education have an estimated WTP of $2.05 USD per gram of birth weight compared with $1.41 for individuals with at least some college education. In both cases, these values are significantly different to zero, however given the small sample of

to have children (p-value: 0.443 in column 3).

[15] When controlling for interactions between birth weight and individual characteristics (Table A6), we obtain similar point (and interval) estimates, and interaction terms are jointly insignificant at typical levels (p-value: 0.983 in column 4).

non-college educated individuals, the confidence intervals of the two groups nearly overlap entirely.

In Appendix Table A8 we additionally consider heterogeneity by race and sex of the respondent. This analysis suggests that those reporting "Other Race" or reporting being Asian have the highest WTP for birth weight followed by individuals reporting being White, and individuals reporting being Black. However the confidence intervals for the average WTP overlap across the various races. We also observe a higher WTP for birth weight among male respondents than among females but with overlapping confidence intervals once again. Clear divergent gender preferences (men preferring boys, women preferring girls) are also documented.

While these should be cast as exploratory analyses, Figure 4 provides some evidence that non-linearity in estimates turning negative at higher birth weights (in line with complications when babies are born at higher weights) are driven more clearly among higher income and college educated groups. In the case of families with a total income of above $55,000 USD, the non-linearity is observed, with WTPs falling from 7lbs, 8oz onwards, while no such reduction is observed among families with total incomes below 55,000 USD. Similarly, while based on noisy estimates, non-linearities are not clearly visible among non-college educated groups, potentially explaining higher WTPs in this group given higher point estimates across the entire birth weight distribution.

5 Assessing the Validity of our Experimental Estimates

Our experimental estimates are subject to two potential limitations. First, they come from a convenience sample of US residents, namely MTurk respondents. As documented in the online appendix Table A2, MTurk users are different from the US population as a whole. Second, our estimates are based on hypothetical choices, and one may be worried about hypothetical bias.[16,17] In order to check the validity of our estimates of the private valuation of birth weight, we compare our WTP for birth weight with that coming from observed behavioral changes owing to the impact of changes in birth timing due to financial incentives faced by parents.

[16]While it has been observed that results from hypothetical choices are nearly always replicated on average in *incentivized* choice experiments (Camerer and Hogarth, 1999), and that these results can agree very closely to true behavior (Hainmueller, Hopkins and Yamamoto, 2013), there are mixed opinions about the appropriateness of using hypothetical choice to value goods in economic research. Alternative perspectives on this are presented by Hausman (2012) and Carson (2012) in a symposium on contingent valuation.

[17]We additionally conduct a test examining whether individuals exhibit preference stability across rounds within the conjoint experiment. As noted in Harris, Gerstenblüth and Triunfo (2018, section 2B), testing preference stability requires holding constant the context of a choice experiment. We thus consider the sub-set of all pairs of profiles that are identical in terms of attributes for sex and season of birth. This lets us isolate changes in birth weight and cost differential between these two comparisons, and observe whether individuals make mutually inconsistent choices. For example, a mutually inconsistent choice would occur if an individual reveals that they are willing to pay p for an increase in birth weight of q given a particular set of sex and season of birth attributes, but then fails to pay p' for an increase in q' where $p/q \geq p'/q'$ when later facing the same sex and season of birth attributes. When we conduct this test, we find a relatively small number of cases where we can formally show that individuals have mutually inconsistent preferences, namely in 26 of the 14,035 pairs considered.

After this comparison, we assess our experimental estimates for private WTP in light of a number of results from the economic literature on birth weight. In particular we ask two questions: Firstly, how does private WTP compare to the WTP inferred from public programs?[18] Secondly, how does the private WTP compare to the total expected (labor market) benefits accruing to birth weight over the life cycle?[19]

5.1 Comparison of Experimental Estimates with Tax Incentives

Schulkind and Shapiro (2014) discuss the impact of tax incentives on birth timing and birth outcomes in the United States. Using their estimates, we can consider what proportion of individuals are incentivized to shift their child's date of birth due to a $1,000 increase in tax incentives as well as what the impact of this incentive is on average birth weight.[20] If we combine Schulkind and Shapiro's estimate that 1 in 134 births are shifted due to a $1,000 tax incentive in the US, and that this shift has an impact of between 2.41-6.37 grams in the population, the scaled increase in birth weight on those who are estimated to change date of birth would be between $2.41 \times 134 = 323$ grams and $6.37 \times 134 = 854$ grams. When expressed in terms of the $1,000 incentive, this suggests that parents exhibit a WTP for birth weight of $1.17-3.09$ per gram.[21]

This range is noteworthy for several reasons. Firstly, it lines up with our experimental estimates from Mechanical Turk of $1.47-$2.40. Secondly, it is obtained from the same country. Finally, it refers to birth weights in a broadly normal range as in our MTurk experiment, given that parents changing the exact date of birth using rescheduled C-sections are those whose babies are in the healthy range, not those in high-risk pregnancies. Thus, it seems that our experimental findings are backed up by choices revealed in real world decisions. Of course, the consideration of tax incentives as a real world "natural experiment" is limited given that it is based on selected *compliers*, namely those parents who are willing to move birth timing based on financial incentives. But our findings suggest that in a controlled, albeit hypothetical, experimental setting similar average results are observed in a convenience sample, i.e., MTurk respondents.

Finally, inherent in the design of the DCE was the decision to focus only on the WTP for

[18] We infer the WTP for birth weight from two large social safety net programs. The first is WIC (the Special Supplemental Nutrition Program for Women Infants and Children), a program which explicitly targets neonatal health, and the second is the Food Stamp Program, which, although not designed to target neonatal health outcomes, has been documented to have important impacts on early-life human capital measures.

[19] While the labor market returns to birth weight are a clear lower bound on the value of birth weight, these are all private returns, and so provide a benchmark value with which to compare the private WTP estimates discussed in the previous section.

[20] In terms of birth timing, Schulkind and Shapiro (2014) state "The estimate in Column (1) of 0.0037 indicates that a $1,000 increase in tax benefits is associated with approximately a 0.37 percentage point increase in the probability of a December birth. This point estimate corresponds to approximately 1 out of every 134 January births being moved to December for a $1,000 increase in tax benefits." And in considering birth weight, they state "Evaluating the point estimate from Column (1) at its 95% confidence intervals suggests that an additional $1,000 in benefits causes between a 0.07% and 0.19% decrease in average birth weight, or between 2.41 and 6.37 g".

[21] These values are given as $1,000/854 grams = $1.17 per gram and $1,000/323 grams = $3.09 per gram.

birth weight over the normal range of weights of 2,500-4,000 grams. While the experimental design precludes the direct estimation of this WTP over the omitted range of low birth weights, Almond, Chay and Lee (2005) estimated hospital costs associated with LBW at $4.93 per gram. A back-of-the envelope calculation, where we take the estimate by Almond, Chay and Lee (2005) as the average WTP for gram of birth weight over the range of *low* birth weights, gives an average WTP of $1.77 per gram.[22]

5.2 Comparison with WTP from Public Programs

It is of interest to ask how estimates of private WTP from this paper compare with the inferred WTP from public investment. While much of the benefits of increases in birth weight accrue to families, increases in birth weight also have important public returns, including benefits flowing from reductions in public health care spending, and lower usage of means-tested public benefits programs (Almond, Chay and Lee, 2005). In the paragraphs below we provide back-of-the-envelope calculations of the implied WTP for birth weight based on public investment. However, we note that when estimating returns using public programs, these should be treated as strict upper bounds given that the benefits of the public programs considered cover a large number of domains beyond simply early life health (refer to Clarke, Cortés Méndez and Vergara Sepúlveda (2020) for additional discussion). Thus, this exercise should be viewed as at best leading to tentative bounds.

Comparison with the Public WTP estimated from a Targeted Program. We can estimate the WTP for birth weight using estimates from the WIC, which provides food and education to pregnant and postpartum breastfeeding women who earn less than 185% of the US federal poverty guideline. By combining estimates of the cost per WIC user with estimates of the benefit in terms of additional birth weight, we can arrive at an estimate of the WTP per gram of birth weight. Ben-Shalom, Moffitt and Scholz (2011) document that WIC participation costs $54 per enrollee per month, and according to WIC administrative data, 56.9%, 34.7% and 7.8% of participants enroll in the first, second or third trimester respectively (Johnson et al., 2013). Using trimester midpoints to calculate months of enrollment, this suggests approximate total costs of covering a single pregnant woman of $321. Among plausibly causal estimates of the impact of the WIC program, Rossin-Slater (2013) estimates that participation has a mean impact of 27 grams of birth weight, and Hoynes, Page and Stevens (2011) estimate impacts of 18-29 grams. In the case of the highest estimated impact, the WTP based on the WIC equates to $321/29 grams = $11.07 per gram, while for the lowest estimate, the WTP equates to $321/18 grams = $17.83 per gram. Both estimates of the WTP based on the WIC exceed our experimental estimates of the private average WTP, for both

[22]This value is calculated as follows: $\$4.93 \times 0.087 + \$1.47 \times 0.913$, where 0.087 and 0.913 are the fractions of low birth weight babies (500-2,499 grams) and normal birth weight babies (2,500-4,000 grams) from the population of US births (see Figure A6).

the whole sample of respondents ($1.47), and the sub-sample of parents ($1.60).

Comparison with the Public WTP estimated from an Untargeted Program. The evidence from WIC discussed above estimates the inferred WTP using a targeted program which explicitly focuses on maternal and newborn health. Nevertheless, there are a range of other public programs which, while not explicitly targeting infant health, have been documented to have unintended effects on these outcomes. Perhaps the largest of these is the Food Stamp Program (or FSP), now known as the Supplementary Nutrition Assistance Program (SNAP), which provided support for 44.2 million people in 2016 at a total cost of 70.9 billion dollars. Almond, Hoynes and Schanzenbach (2011) provide a particularly well-identified estimate of the effect of the FSP on infant health, and in particular, on birth weight. They estimate individual effects of program exposure, which amount to 20.27 grams for white pregnant women or 31.69 grams for black pregnant women. This allow us to estimate the inferred WTP based on the FSP for a gram of birth weight when combined with the costs per pregnant women. In order to determine the costs per pregnant women, we focus on data on current costs and users (in order to be comparable to our estimated WTP in current dollars). Using the final three months of pregnancy to estimate the typical costs for a pregnant woman, and average per person monthly costs from 2016 of $134 (i.e., (71000/44)/12), the inferred WTP based on the FSP for an additional gram in birth weight is approximately $17.[23] Once again, the inferred WTP based on the FSP exceeds our estimates for the average private WTP by an order of magnitude.

5.3 Comparison with the Returns to Birth Weight in the Labor Market

It is well accepted that higher birth weight is associated with reductions in morbidity and mortality, and greater educational attainment and achievement throughout childhood.[24] Moreover, these impacts have been well-documented to persist into adulthood and impact labor market outcomes (Bharadwaj, Lundborg and Rooth, 2015). In Table 5 we review the range of papers which have estimated the long-run returns to birth weight in the US.[25] One way to benchmark (lower bounds) of the parental average WTP for birth weight is to determine how it compares to the flow of expected benefits during the life of their child. Thus, considering these well-estimated cases of

[23]This is calculated using $(134 \times 3)/31.69 = \$12.7$ based on Almond, Hoynes and Schanzenbach (2011)'s estimates for black mothers and $(134 \times 3)/20.27 = \$19.8$ for estimates for white mothers. In addition, we know that 40.2% of food stamp users are white and 25.7% are black (Gray, 2014). Hence, we can get a weighted average estimate using $40.2/65.9 = 0.61$ as the weight for white mothers, and $25.7/65.9 = 0.39$ as the weight for black mothers. This leads us to a weighted average of $\$17 = 0.61 \times \$19.8 + 0.39 \times \$12.7$.

[24]For example, on morbidity, Conley, Strully and Bennet (2003), Almond, Chay and Lee (2005), Oreopoulos et al. (2008), and Gupta, Deding and Lausten (2013), and on early-life education, Lin and Liu (2009), Fletcher (2011), Torche and Echevarría (2011), Figlio et al. (2014), and Bharadwaj, Eberhard and Neilson (2017), demonstrate a strong and plausibly causal link.

[25]A number of similar estimates exist in a non-US setting (for example Rosenzweig and Zhang (2013) in China, Black, Devereux and Salvanes (2007) in Norway, and Currie and Hyson (1999) in Great Britain), however in order to benchmark our WTP results in the US population we do not focus on these here.

the labor market returns to birth weight, we can discount expected returns back to the start of an individual's life, and compare it with our experimentally estimated WTP. This should of course be considered as a lower bound to the true value of birth weight.[26]

For this exercise, we are most interested in those papers which provide estimates of the long-run returns to birth weight in the labor market. Among those papers which have estimated the effect of birth weight on earnings, there are three papers that use twin or sibling fixed effects to leverage within family variation in birth weight to estimate returns conditional on genetic material. These are Behrman and Rosenzweig (2004), Johnson and Schoeni (2011), and Cook and Fletcher (2015). In order to generate a back-of-the-envelope comparison of the WTP for birth weight with the present value of expected labor market returns, we focus on the estimates of Behrman and Rosenzweig (2004). Behrman and Rosenzweig (2004)'s results provide a point estimate of the labor market returns to birth weight in the US which suggests that "augmenting a child's birth weight by a 1 lb. increases her adult earnings by over 7%". According to the United States Census Bureau (2016), the median personal income in the US in 2015 was \$30,240. If we assume a working life which begins at the age of 25 and ends at the age of 60, we can calculate the present value of a 7% increase in wages as a deferred annuity. This calculation suggests that the present value of an additional pound of birth weight is \$10,235.[27] Dividing this value by the 454 grams in a pound gives the labor market value of a gram of weight of \$23. If we assume that only approximately 60% of the working age population will actually be employed in the labor market (United States Bureau of Labor Statistics, 2017), scaling by this value still suggests a labor market return of approximately \$14, an order of magnitude higher than our estimated values of average WTP.

This lower bound calculation using Behrman and Rosenzweig (2004)'s estimates relies on a number of assumptions that are unlikely to hold in practice. Chief among these is that the returns to birth weight are stable over the life course, and salary and labor market participation rates are also stable over the life course. Still, we believe this is an informative estimate, if only because the \$14 per gram is close to the WTP inferred from WIC and FSP (\$11-\$18 per gram), but 8-13 times larger than the private average WTP estimated among our respondents.

[26] Labor market returns are a convenient financial metric, but do not include any of the additional pecuniary or non-pecuniary benefits which may flow to parents from a higher birth weight child such as lower expected costs associated with medical care (Almond, Chay and Lee, 2005) and the clear intrinsic value of health at birth, regardless of its impacts on economic circumstance during later life.

[27] We calculate the present value as

$$PVBW = (\$30,240 \times 0.07) \times \frac{1-(1+0.05)^{-35}}{0.05} \times \frac{1}{(1+0.05)^{25}} = \$10,235.46.$$

Note that in general, if anything our assumptions are conservative with regards to the estimated present value. For example, if we were not to discount this amount back to the age of 0, or if we were to discount using a lower discount rate to incorporate inflation, this would lead to higher calculated present values.

6 Allowing for Preference Heterogeneity

Our empirical analysis has used a traditional logit model, which assumes that the parameter associated with each birth attribute is *fixed* across individuals. In our case, this is tantamount to assuming *homogeneous* preferences over birth outcomes between individuals. In this subsection we allow for preference *heterogeneity* in birth outcomes during our estimation process by specifying a *mixed* logit model (Revelt and Train (1998), McFadden and Train (2000) and Train (2003)).

This procedure requires the use of a maximum simulated likelihood in place of maximum likelihood, however is now available in many standard software packages.[28] The parameter vector now consists of each individual's specific parameters, which give rise to the mean parameter in the sample as well as measures of its variance.

In the online appendix Table A9 we display the parameters estimated from the mixed logit, as well as the WTP for birth weight using the full sample and each sub-sample of interest. As is common in discrete choice applications with willingness to pay, we model the price (out of pocket expenses) as *fixed* across respondents, while allowing all other coefficients (and preferences) to *vary*. This ensures that the WTP for each attribute is identified, as outlined in Revelt and Train (1998). In panel A we display the mean estimates for each parameter, and in panel B the standard deviation of each parameter. As is typical with the mixed logit, the normalization of the parameters with respect to individual utility means that point estimates are significantly larger than those in the standard logit model. Nevertheless, we are more interested in the WTP of each parameter (as well as the distribution of parameters in the sample) rather than each parameter itself. *On average*, the WTP for birth weight is quite similar to that estimated in the standard logit model. For the full sample the WTP from the Mixed Logit model is \$1.68 per gram (95% CI: [\$1.47, \$1.90]). Similarly, we observe that this WTP is highest for parents at \$1.79 per gram (95% CI: [\$1.48, \$2.11]), followed by non-parents who plan to have a birth (\$1.72 per gram, 95% CI: [\$1.29, \$2.15]) and the lowest among non-parents who do not intend to have children (\$1.38 per gram, 95% CI: [\$0.99, \$1.77]).

Using both of these sets of parameters (mean and standard deviation), we are also able to determine the proportion of all respondents who positively value birth weight (and indeed any characteristic) in these linear specifications.[29] These values are displayed at the base of the table, indicating what proportion of respondents positively value birth weight. These values follow a similar pattern as those observed for WTP. Namely, parents and non-parents who intend to have children are the most likely to place a positive value on birth weight (70.7% and 71.0% respectively), while non-parents who do not plan to have children are the least likely to assign a positive value

[28] See for example Hole (2007*b*) for a Stata implementation, or a series of packages made available by Kenneth Train in other languages (`https://eml.berkeley.edu/~train/software.html`).

[29] These can be calculated using the entire vector of parameters, or alternatively as $100 \times \Phi(-\mu_k/\sigma_k)$, where Φ is the cumulative normal distribution, μ_k is parameter k's mean, and σ_k is its standard deviation.

(68.1%). Using the conditioning of individual taste (COIT) method described in Revelt and Train (2000) we are able to estimate the entire distribution of WTP across respondents, which we display in the online appendix Figure A9. This provides evidence of considerable heterogeneity in tastes for birth weight.

Finally, we extend the Mixed Logit to our non-parametric specification where birth weight enters in categories as observed by respondents. The results for the WTP, as well as the percent of respondents who value each birth weight positively, are displayed in the online appendix Figure A10. These are all based on the mean and standard deviations of the parameters estimated from the mixed logit, as displayed in the footer of Table A9. In turning to the proportion of respondents who positively value each birth weight category, we observe that this quickly rises as birth weights diverge from the baseline reference category. Once reaching approximately 2,800 grams, over 80% of all respondents prefer this to the baseline value of 2,500 grams, and this value rises to close to 100% once exceeding approximately 2,950 grams.

All in all, our experimental private WTP estimation is robust to allowing for preference heterogeneity.

7 Conclusion

The use of birth weight as an individual's prominent measure of early-life endowment of human capital is now a well established practice in the economic literature. Birth weight has increasingly been shown to be a modifiable outcome, being particularly responsive to certain policy measures. Despite considerable public investment in policies to increase birth weight and health at birth, very little is known about the *private* willingness to pay for birth weight.

In this paper we document that individuals have a positive, economically and statistically significant WTP for birth weight. We find that this WTP is higher among parents than non-parents, and higher among non-parents that intend to have children than among non-parents who do not intend to have children. Among all respondents the average WTP for a gram of birth weight is estimated at $1.47, while among parents is estimated at $1.60. The average WTP based on non-parametric estimates among all respondents is estimated at $2.40 per gram.

While our experimental findings are based on hypothetical choices made by a convenience sample of respondents (MTurk workers), our range of estimates lines up with the WTP for birth weight inferred from the impact of tax incentives on birth timing and birth outcomes in the United States as reported in Schulkind and Shapiro (2014). Using the estimates from these authors, we compute the WTP for birth weight among parents who were willing and moved birth timing based on financial incentives at $1.17-$3.09 per gram.

Our findings suggest that parents have a WTP of about $1.60 per gram of birth weight, far too little in comparison to the lower-upper bounds of $14-$17 per gram implied from private returns and public investment. Whether this is a behavioral puzzle, is driven by imperfect altruism, or is due to the fact that these returns are simply the means of a very random process and so accounting for dispersion in the returns (risk) would lead any rational parent to have a much lower WTP is something that should be taken up in future research.

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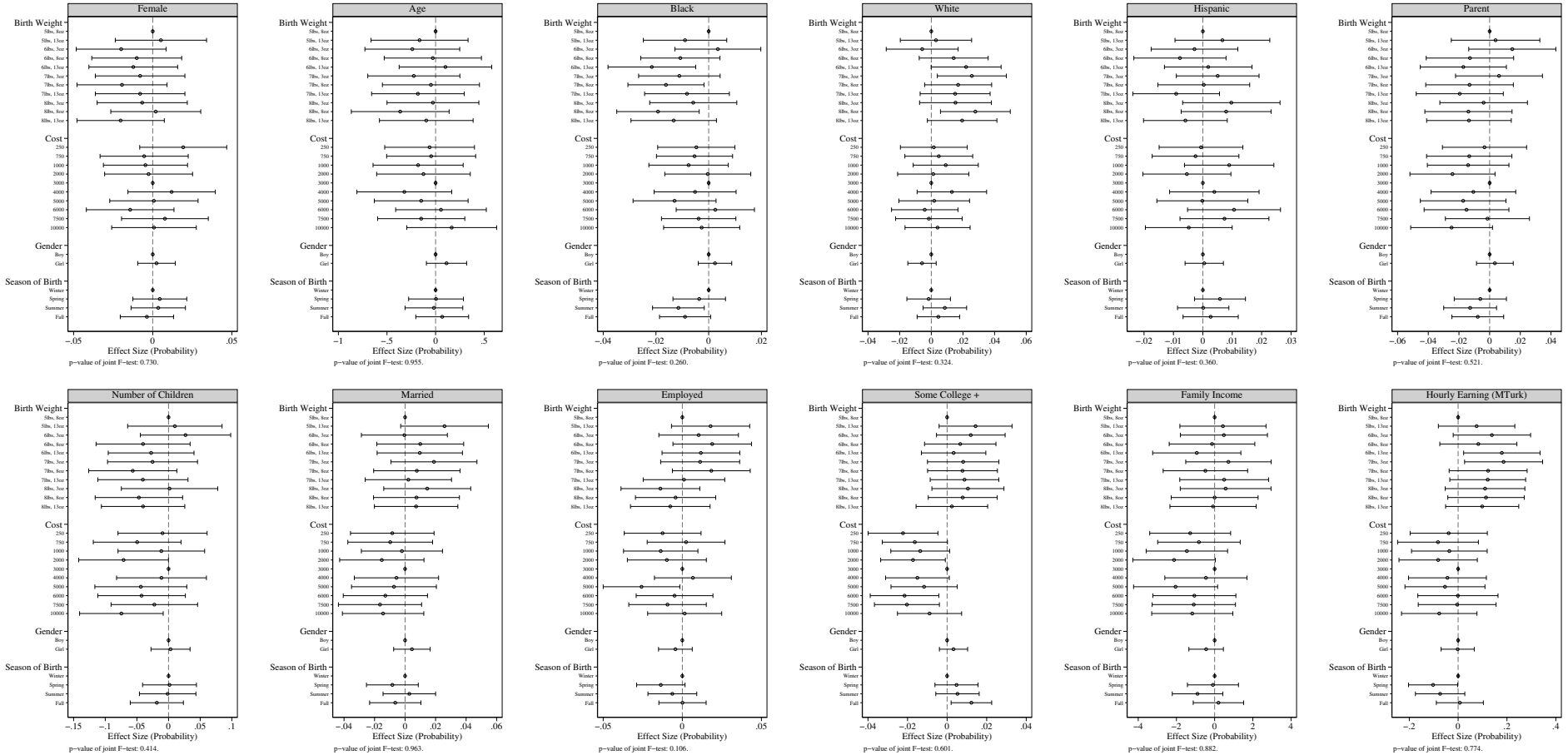
Figures and Tables

Table 1: Summary Statistics of Respondents

	N	Mean	Std. Dev.	Min	Max
Female	1894	0.53	0.50	0.00	1.00
Age	1894	36.55	11.68	18.00	82.00
Black	1894	0.08	0.27	0.00	1.00
White	1894	0.82	0.38	0.00	1.00
Hispanic	1894	0.08	0.27	0.00	1.00
Parent	1894	0.50	0.50	0.00	1.00
Non-Parent Intending Children	955	0.47	0.50	0.00	1.00
Number of Children	1894	1.01	1.27	0.00	6.00
Married	1894	0.45	0.50	0.00	1.00
Employed	1894	0.73	0.44	0.00	1.00
Some College +	1894	0.89	0.31	0.00	1.00
Years of Education	1894	14.67	1.73	8.00	17.00
Total Family Income (1000s)	1894	59.63	39.29	5.00	175.00
Hourly earnings on MTurk	1894	4.43	2.85	1.50	11.50

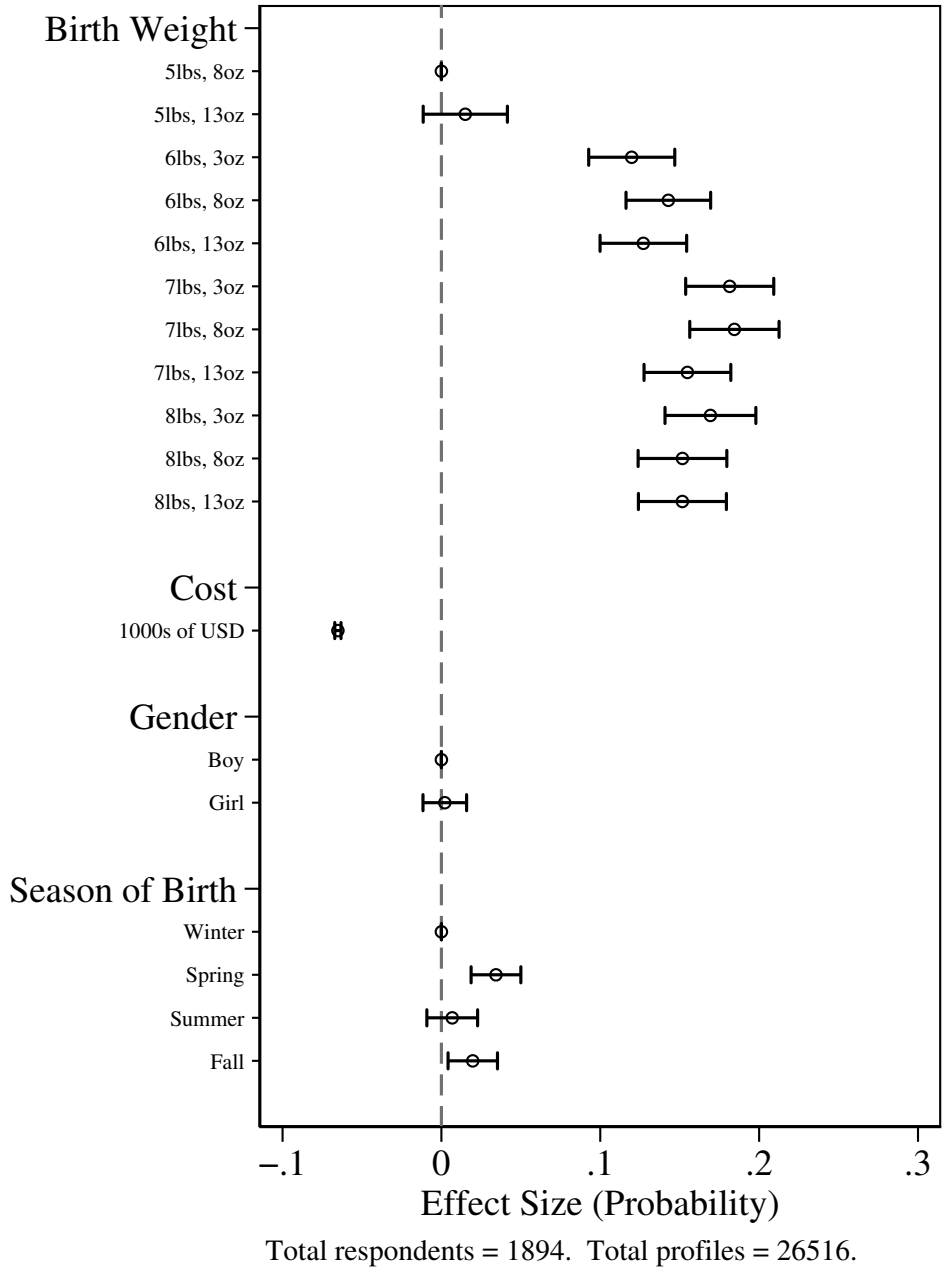
NOTES: Refer to Online Appendix Figure A1 for a discussion of the experimental sample. Years of education, total income and hourly MTurk earnings are calculated from categorical variables. Non-Parent Intending Children refers to any respondent who either answers that they are pregnant or intend to have children, and currently have no children.

Figure 1: Balance Tests



NOTES: Point estimates and confidence intervals are plotted, documenting whether respondents with a particular observable characteristic were more likely to observe particular attributes in conjoint experiments. Variables described in Table 1 are regressed on whether the respondent observed each possible attribute in the experiment. The observable variable (dependent variable) in each case is indicated in plot titles. In each plot, 95% confidence intervals are reported for each attribute in the experiment, and the omitted category for each characteristic is indicated as a point at 0. Each plot represents a separate regression, and the p-value of an Omnibus F-test for each regression is reported at the base of each plot.

Figure 2: Discrete Choice Experimental Results



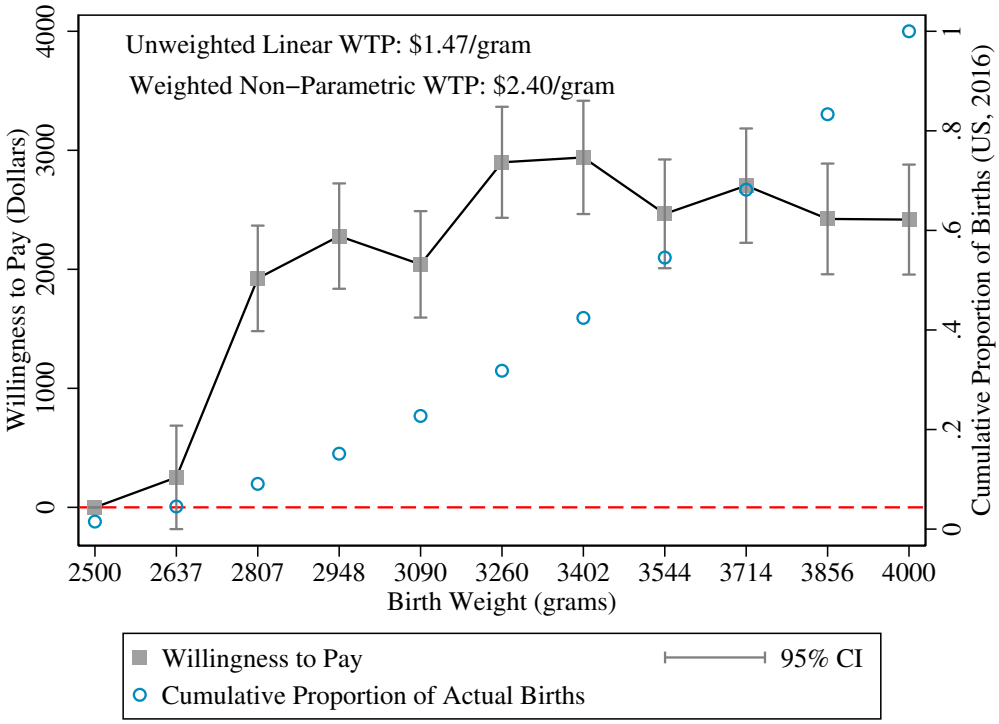
NOTES: Point estimates and confidence intervals are displayed of the change in likelihood of choosing a birth profile given that a particular characteristic was seen. Each characteristic is compared to the omitted base case indicated on the zero line. Each respondent observes 7 paired birth scenarios, resulting in 14 profiles per respondent. 95% confidence intervals are clustered by respondent, and costs are displayed as a linear coefficient. Fully non-parametric costs are displayed in Appendix Figure A7.

Table 2: Birth Characteristics and Willingness to Pay for Birth Weight

	(1) Continuous	(2) Categorical
Birth Weight (in 1000s of grams)	0.092***	
	[0.007]	
costNumerical	-0.063***	-0.063***
	[0.001]	[0.001]
5lbs, 13oz		0.016
		[0.014]
6lbs, 3oz		0.120***
		[0.014]
6lbs, 8oz		0.143***
		[0.014]
6lbs, 13oz		0.128***
		[0.014]
7lbs, 3oz		0.181***
		[0.014]
7lbs, 8oz		0.184***
		[0.014]
7lbs, 13oz		0.154***
		[0.014]
8lbs, 3oz		0.169***
		[0.015]
8lbs, 8oz		0.152***
		[0.014]
8lbs, 13oz		0.151***
		[0.014]
Girl	0.003	0.002
	[0.007]	[0.007]
Spring	0.034***	0.034***
	[0.008]	[0.008]
Summer	0.006	0.006
	[0.008]	[0.008]
Fall	0.019**	0.019**
	[0.008]	[0.008]
WTP for Birth Weight (1000 grams)	1470.3	2401.0
95% CI	[1238.3;1702.3]	[2032.4;2769.6]
Observations	26516	26516

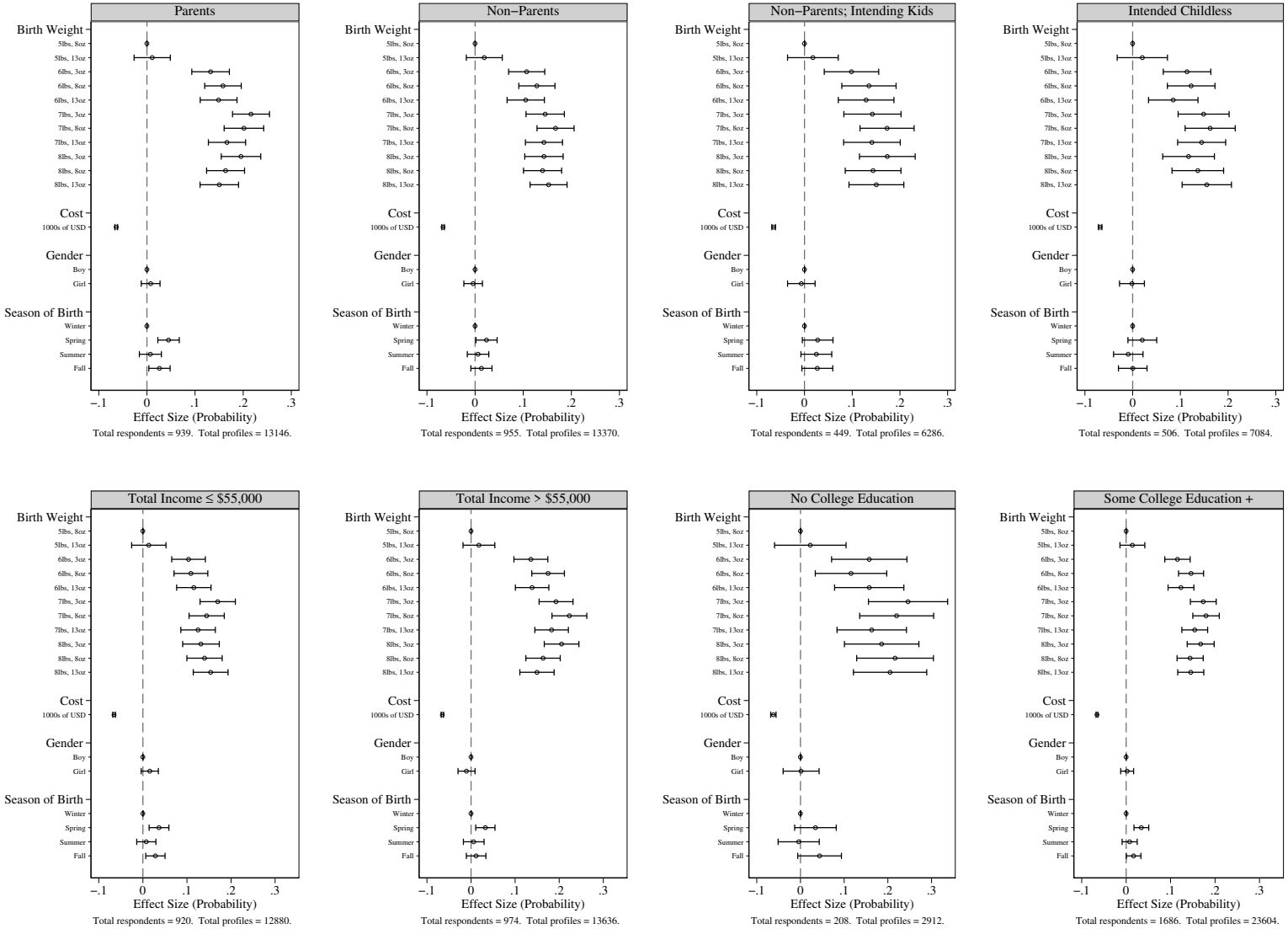
Average marginal effects from a logit regression are displayed. All columns include option order fixed effects and round fixed effects. Standard errors are clustered by respondent. Willingness to pay and its 95% confidence interval is estimated based on the ratio of costs to the probability of choosing a particular birth weight. The 95% confidence interval is calculated using the delta method for the ratio.

Figure 3: Relative Willingness to Pay for Birth Weight



NOTES: Each point and confidence interval are with respect to the baseline (omitted) category of 2,500 grams, the minimum displayed birth weight. Willingness to pay is determined as the ratio between the particular birth weight and out of pocket costs estimated as average marginal effects in a logit regression. "Cumulative proportion of births" refers to the cumulative proportion in the displayed weight range of 2,500 to 4,000 grams. 95% confidence intervals displayed are calculated using the delta method.

Figure 4: Heterogeneity



NOTES: Methods are identical to those described in notes to Figure 2. The full sample is split by parents or non-parents (panels A and B), and then non-parents are split into those who report intending to have children (or already being pregnant) versus those who do not intend to have children "Intended Childless" (panels C and D). Panels E and F compare responses for respondents reporting a total family income of 55,000 USD or lower with those reporting a total family income above 55,000 USD, and panels G and H present estimates by whether or not the individual has attained any college education.

Table 3: Birth Characteristics and Willingness to Pay for Birth Weight by Parental Status

	All	Parent		Non-Parents	
	(1)	(2) Yes	(3) No	(4) Intending	(5) Not Intending
Birth Weight (in 1000s of grams)	0.092***	0.098***	0.086***	0.092***	0.082***
	[0.007]	[0.010]	[0.010]	[0.014]	[0.013]
costNumerical	-0.063***	-0.061***	-0.064***	-0.062***	-0.065***
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
Girl	0.003	0.009	-0.004	-0.007	-0.001
	[0.007]	[0.010]	[0.010]	[0.015]	[0.013]
Spring	0.034***	0.046***	0.024**	0.026	0.021
	[0.008]	[0.011]	[0.011]	[0.016]	[0.015]
Summer	0.006	0.007	0.005	0.023	-0.009
	[0.008]	[0.012]	[0.011]	[0.016]	[0.016]
Fall	0.019**	0.026**	0.012	0.026	-0.000
	[0.008]	[0.011]	[0.011]	[0.016]	[0.015]
WTP for Birth Weight (1000 grams)	1470.3	1598.2	1353.5	1476.8	1254.1
95% CI	[1238.3;1702.3]	[1255.4;1941.1]	[1038.5;1668.5]	[1010.4;1943.2]	[826.4;1681.9]
Observations	26516	13146	13370	6286	7084
p-value for test of equality			0.501		0.676
p-value for equality (2)=(5)					0.419

Average marginal effects from a logit regression are displayed. All columns include option order fixed effects and round fixed effects. Standard errors are clustered by respondent. Willingness to pay and its 95% confidence interval is estimated based on the ratio of costs to the probability of choosing a particular birth weight. The 95% confidence interval is calculated using the delta method for the ratio. Intending and Not Intending in columns 4 and 5 refer to decisions regarding future children as outlined in Table 1. Tests of equality in the table footer refer to equality of WTP estimates between columns (2) and (3) and between columns (4) and (5) in the first test, and between WTPs estimated between columns (2) and (5), that is between parents and intended childless, in the second test. These p-values are directly estimated using a Chow test.

Table 4: Birth Characteristics and Willingness to Pay for Birth Weight by SES Status

	All	Family Income		College	
	(1)	(2)	(3)	(4)	(5)
		$\leq$ \$ 55,000	$>$ \$ 55,000	None	Some +
Birth Weight (in 1000s of grams)	0.092***	0.085***	0.098***	0.122***	0.089***
	[0.007]	[0.010]	[0.010]	[0.022]	[0.007]
costNumerical	-0.063***	-0.063***	-0.062***	-0.059***	-0.063***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.001]
Girl	0.003	0.016	-0.010	-0.000	0.003
	[0.007]	[0.010]	[0.010]	[0.021]	[0.007]
Spring	0.034***	0.038***	0.031***	0.034	0.034***
	[0.008]	[0.011]	[0.011]	[0.024]	[0.008]
Summer	0.006	0.008	0.005	-0.005	0.007
	[0.008]	[0.011]	[0.012]	[0.024]	[0.009]
Fall	0.019**	0.029***	0.010	0.042	0.016*
	[0.008]	[0.011]	[0.011]	[0.026]	[0.008]
WTP for Birth Weight (1000 grams)	1470.3	1357.6	1577.0	2045.2	1407.6
95% CI	[1238.3;1702.3]	[1028.3;1686.9]	[1249.7;1904.2]	[1250.0;2840.5]	[1165.4;1649.8]
Observations	26516	12880	13636	2912	23604
p-value for test of equality			0.784		0.373

Average marginal effects from a logit regression are displayed. All columns include option order fixed effects and round fixed effects. Standard errors are clustered by respondent. Willingness to pay and its 95% confidence interval is estimated based on the ratio of costs to the probability of choosing a particular birth weight. The 95% confidence interval is calculated using the delta method for the ratio. Estimates are presented separating by family income and by respondent educational level. Tests of equality in the table footer refer to equality of WTP estimates between columns (2) and (3) and between columns (4) and (5), that is testing for equality of WTP by income and by educational level. These p-values are directly estimated using a Chow test.

Table 5: Estimates of the Long Run Returns to Birth Weight in the US

Authors	Weight	Geographic Area	Time Period	Dependent Variable	Estimated Return	Denominator	Estimation Strategy
Panel A: Labor Market							
Behrman and Rosenzweig (2004)	$\mu = 90.2$oz ($\mu = 2,557$)	Minnesota	1936-1955	ln(Wage)	0.190(0.077)[a]	oz/week pregnancy	Between MZ twin
Cook and Fletcher (2015)	$\mu = 3,367$	Wisconsin	1957 HS graduates	ln(Wage)	0.0997(0.0788)	Birth Weight (1 sd)	Between siblings
Johnson and Schoeni (2011)	NA	USA (PSID)	1951-1975	ln(Earnings)	-0.1667(0.097)	LBW	Between siblings (males only)
Panel B: Completed Education							
Royer (2009)	$\mu = 2,533$	California	1960-1982	Completed Education (Years)	0.16(0.07)	1,000g (3500-2500g)	Between twins (females only)
Currie and Moretti (2007)	$\mu = 3,268$	California	1970-1974	Completed Education (Years)	-0.079(0.014)	LBW	Between siblings (females only)
Conley and Bennett (2000)	Pr(LBW) =0.07	USA (PSID)	1968-1973	Timely Graduation	-2.024(0.764)	LBW	Between siblings

[a] Standard error is calculated based on t-statistic reported in original paper.