The Effect of Prenatal Care on Birthweight: A Full-Information Maximum Likelihood Approach*

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ABSTRACT

This paper takes a unique approach to estimating the relationship between birthweight and prenatal care. We use a multi-equation, full-information maximum likelihood estimation method, Discrete Factor Analysis, to control for the potential biases surrounding both the sample-selection of the pregnancy-resolution decision and the endogeneity of prenatal care. Few studies have attempted to control for both sample-selection and endogeneity in birthweight outcomes, and this is the first study to apply Discrete Factor Analysis in this area. In addition, we utilize the actual number of prenatal care visits; other studies have normally measured prenatal care as the month care is initiated. We estimate a birthweight production function using 1993 data from the US state of Texas. The results underscore the importance of correcting for estimation problems. Specifically, a model that does not control for sample-selection and endogeneity overestimates the benefit of an additional visit for women who have relatively few visits. This overestimation may indicate "positive fetal selection": women who carry their fetuses to term may have healthier babies. In addition, a model that does not control for self-selection and endogenity predicts that an additional visit past approximately 20 leads to lower birthweight, while a model that corrects for these estimation problems predicts a positive affect for up to 50 visits. This result may pick up the effect of mothers with less healthy fetuses making more prenatal care visits. Specifically, we observe the "adverse selection" in prenatal care found in other studies.

I. Introduction

In recent years a number of empirical studies have indicated that earlier initiation of prenatal medical care leads to increases in birthweight, a commonly used proxy for infant health (McCormick, 1985; Kleinman and Kessel, 1987). Unfortunately, estimating the relationship between birthweight and prenatal care is extremely problematic. One estimation problem that arises is the sample-selection associated with the pregnancy-resolution decision: A pregnant woman's decision to give birth or have an abortion may be correlated with unobservable factors that influence both the use of prenatal care (a health input) and birthweight. For example, sample-selection may positively affect birthweight and prenatal care use if women who practice healthier behavior during pregnancy, like eating more nutritiously or regularly exercising, are also more likely to give birth. Therefore, estimates of either birthweight outcomes or the demand for prenatal care contain a sample-selection bias if women who chose to give birth constitute a non-random sample of pregnant women.

Another estimation problem is that measures of prenatal care use, or other observed inputs to the birthweight outcome, are endogenous if there are unobservable factors that determine the mother's prenatal care behavior as well as the infant's birthweight. For instance, women with inferior health endowments, the exogenous health component unobservable to the researcher, may expect problematic pregnancies (e.g., lower birthweight) and thereby seek more prenatal care during their pregnancies. In this case, neglecting endogeneity may either underestimate any positive impact of prenatal care or indicate that additional prenatal care actually reduces birthweight. Alternatively, women who make more prenatal care visits may also practice other forms of healthy behavior that raise birthweight. Thus, failing to account for the endogeneity of prenatal care use could overstate the benefits of prenatal care. Ultimately, both the sample-selection and endogeneity biases are caused by unobserved factors (referred to as "unobserved heterogeneity biases") that affect the pregnancy-resolution decision, the use of prenatal care, and birthweight.[1]

This paper takes a unique approach to estimating the relationship between birthweight and prenatal care use. First, we use a full-information maximum likelihood estimation method, Discrete Factor Analysis, to control for the potential biases surrounding both the sample-selection of the pregnancy-resolution decision as well as the endogeneity of prenatal care use. Discrete Factor Analysis does not make restrictive assumptions that the error term is multivariate parametric; instead, it estimates the true distribution of the unobserved variables that are correlated with the error term. Previous birthweight studies implicitly assume that this correlation is normally distributed. This assumption is potentially problematic if the distribution in not normal. Discrete Factor Analysis has been shown to be a more appropriate estimator when the underlying distribution of the unobserved variables is non-normal.

[1] See Grossman and Joyce (1990) for a detailed explanation of these unobserved heterogeneity issues.

Second, this paper uses a comprehensive data set on individual pregnancies from the state of Texas. These data were collected for all reported pregnancies during 1993 in the 254 Texas counties; 235 of these counties were without an abortion provider, 34 were without publicly-supported family planning services, and 167 were without OB/GYN medical doctors. Therefore, these data provide an opportunity to analyze the relationship between birthweight and prenatal care use. Third, we estimate the effect of the number of prenatal visits, rather than delay of prenatal care initiation, on birthweight. Past research has focused on the month that prenatal care was initiated during pregnancy to measure prenatal care use. The implicit assumption seems to be that once women initiate prenatal care, they are "in the system" and will receive the optimal amount of care during their pregnancy. Initiation of prenatal is important, but does not fully proxy the prenatal care experience of each woman.[2] Furthermore, including the number of visits allows us to estimate the marginal benefit of a prenatal care visit.

Previous Research

The empirical literature focusing on infant health and prenatal medical care has been plagued with the problems surrounding the biases introduced by health heterogeneity and sample-selection of the pregnancy-resolution decision (Harris, 1982). Rosenzweig and Schultz (1982, 1983, 1988) are the first to estimate birthweight production functions with two-stage least squares (2SLS) to account for the effect of health heterogeneity on usage of health inputs, e.g., prenatal care. Using national samples of individual-level data, the authors find that delaying the onset of prenatal care reduces birthweight. In addition, they find that OLS underestimates the effect of delaying prenatal care on birthweight by as much as 40 times their 2SLS estimates. The authors also estimate various functional forms of the birthweight production function.

[2] In our sample from Texas, the number of visits ranges from zero to 49 with a mean of 11.44 and a standard deviation of 4.18. Even conditioned on month of initial visit, substantial variation exists.

Accounting for heterogeneity is shown to be more important than functional form in predicting birthweight. The authors find evidence of "adverse selection" in prenatal care; namely, unhealthy women initiate earlier prenatal care and their babies have lower birthweight. Rosenzweig and Schultz, however, ignore the sample-selection associated with the pregnancy-resolution decision on infant health.

Joyce (1993) estimates a model with sample-selection and endogenous switching using individual-level data from New York City separated by race. The author shows that more "adequate" prenatal care leads to higher birthweight. OLS again underestimates the effect of prenatal care on birthweight across all races. The results indicate adverse selection in prenatal care demand, since the least healthy women are more likely to have adequate prenatal care. Rosensweig and Wolpin (1991) use the National Longitudinal Survey of Youth (NLSY) to study the effect of maternal behaviors, including initiation of prenatal care, on birthweight. The authors use a within-mothers fixed-effects estimator to control for unobserved heterogeneity in maternal health. The results indicate that early initiation of prenatal care increases birthweight. Also, 90 percent of the variance in birth outcomes is attributable to the unobserved health endowment of the mother. Currie and Cole (1993) use the NLSY to estimate a "reduced-form" birthweight equation to avoid the problems of identifying the structural equations of a birthweight production function. Currie and Cole indicate that delaying initiation of prenatal care has a negative, albeit insignificant, effect on birthweight. Each of these three studies ignores sample-selection effects of the pregnancy-resolution decision on infant health.

The literature indicates that prenatal care has important impacts on infant health. However, several studies also have shown that the pregnancy-resolution decision influences infant health. Corman, Joyce, and Grossman (1987) use US county-level data to investigate the relationship between health inputs, abortion, and neonatal mortality. The authors find that counties with higher rates of early-initiated prenatal care have lower rates of neonatal mortality, mostly due to reduced likelihood of low birthweight. In addition, the authors give evidence that the abortion decision is correlated with higher birthweight due to "positive fetal selection," i.e., women with the healthiest fetuses are most likely to give birth rather than abort. Their results highlight the importance of the pregnancy-resolution decision in influencing birth outcomes. Joyce (1987) finds some evidence of positive fetal selection using US county-level data to investigate the relationship between prenatal care, abortion, and measures of infant health.

Joyce and Grossman (1990) attempt to estimate the structural relationship between birthweight production functions, the pregnancy-resolution decision, and prenatal care usage. To our knowledge, theirs is the only paper to estimate an infant health production function while simultaneously controlling for sample-selection in pregnancy resolution and the endogeneity of prenatal care usage. Joyce and Grossman use a sample of birth outcomes in New York City to find that women who are more likely to abort a given pregnancy are also more likely to initiate prenatal care later in their pregnancy; this effect is most significant for minority women. Thus, their paper highlights the important of including information on the pregnancy-resolution decision when estimating the effect of prenatal care on birth outcomes. Moreover, the authors find that earlier initiation of prenatal care leads to higher birthweight, but this effect is only significant for black women. In addition, 2SLS estimates treating prenatal care as endogenous lead to larger estimates of the effect of prenatal care on birthweight. Using the Heckman selectivity correction, the authors find that the abortion decision only influences birthweight of black infants. Thus, the decision of black women to give birth appears to be correlated with healthy behavior and improved birth outcomes.

As Grossman and Joyce indicate, samples from New York City have unique socioeconomic and demographic characteristics so that their results cannot be generalized to other geographical areas. In particular, New York City exhibits relatively high levels of availability of abortion providers and high abortion rates, has readily accessible modes of public transportation, and has few state-level restrictions on abortions. Therefore, the full cost of acquiring an abortion (comprised of the dollar cost, availability-induced travel cost, plus any physic cost) is relatively low for New York residents. The unique characteristics of New York City data underscore the importance of complimenting the authors' work with birthweight estimates using data from other geographical regions, particularly areas with wider variations in the availability of those medical services that influence infant health.

Following the general spirit of the Grossman and Joyce (1990) methodology, our paper estimates a birthweight production function accounting for both sample-selection in pregnancy resolution and endogeneity of prenatal care use. However, our paper makes additional contributions to the literature. First, we incorporate a more sophisticated estimation technique, Discrete Factor Analysis, to control for the biases surrounding both the sample-selection as well as the endogeneity of prenatal care use. Discrete Factor Analysis estimates the true distribution of the unobserved variables that are correlated with the error term – instead of making more-restrictive assumptions about this correlation – and has been shown to be a more appropriate estimator when the underlying distribution of the unobserved variables is non-normal. Second, we estimate the effect of the number of prenatal care visits on birthweight. Third, we use a more comprehensive data from pregnancies in the state of Texas during 1993. These data from Texas include women from a wide range of geographic, socioeconomic, and racial characteristics.

II. Methodology

The most common measure of prenatal care usage in the literature appears to be the month of initiation of prenatal care. However, month of initiation is only a part of overall prenatal care usage: It is important to get women into the prenatal care system, and it is important to keep them there. Kotelchuck (1994a) discusses two aspects of prenatal care: (1) month of initiation and (2) percent of recommended visits received. Since the number of prenatal care visits is also an important issue, we supplement past research by estimating our model using the number of prenatal care visits as the measure of prenatal care usage. In addition, using the number of prenatal care visits allows us to measure the marginal effect of an additional visit, which may be important to policy makers who are designing programs to retaining women in the system. Measuring prenatal care using the number of visits also allows us to include a much wider range of interaction terms and to simulate the production of birthweight as a function of prenatal care visits.

The Texas Department of Health released data from all birth certificates during 1993. These certificates contain information on birthweight, mother's pregnancy history, county of residence, consumption of alcohol and cigarettes, age, education, and the number of prenatal care visits. These data were augmented with confidential information on all abortions performed in Texas during 1993. The Texas Abortion Facility Reporting and Licensing Act requires that all abortion providers submit annual data on each abortion performed to the Texas Department of Health. Collection of these data began in 1990, and these data include the patient's age, county of residence, race, and number of previous abortions and live births.

Over 400,000 pregnancies were reported in Texas during 1993 – approximately 320,000 births and 90,000 abortions for women who reside in Texas. There were also about 2,000 fetal deaths reported in Texas in 1993 that are excluded from the estimation. Mainly for ease of computation, we take a randomized sample of 49,209. The three largest racial groups in Texas are Whites, Blacks, and Hispanics of Mexican origin. We expect Black women to have lower birthweight babies; this is the result found in most of the literature, although there are no clear explanations for this result (Cramer, 1987). We choose to analyze Hispanics of Mexican origin rather than all Hispanics: Hispanics of Mexican origin represented 73 percent of all births to Hispanics in Texas in 1993, and there are well-documented differences in birth outcomes among Hispanic groups with different geographic origins (Kleinman and Kessel, 1987). As is the case with most other studies, women under 20 years of age are excluded to minimize simultaneity problems associated with the joint decision of giving birth, marrying, and education. Table One gives summary statistics. Data descriptions and sources are listed in Appendix A. [3]

{INSERT TABLE ONE}

Pregnancy Resolution Equation

The first equation models the probability that a woman has an abortion, controlling for sample selection. The pregnancy-resolution decision is specified as equation (1), a logit equation in which the dependent variable is the log odds that woman *i* carries her pregnancy to term (T = 1) relative to aborting her pregnancy (T = 0). Using the logit specification, birth resolution is modeled as:

$$(1) \qquad ln\left[Prob\ (T_i = 1)/Prob\ (T_i = 0)\right] = \alpha_1 + \beta_1 X_i$$

where the log of the ratio of the odds that a mother will carry her fetus to term is estimated – where $T_i = 1$ if the fetus is carried to term and $T_i = 0$ otherwise. In equation 1, X_i is a vector of explanatory variables that affect the demand for abortion. α_1 and β_1 represent a set of regression parameters to be estimated.

The potential sample-selection surrounding the pregnancy-resolution decision is

[3] Women whose infants have higher gestational ages likely have had more prenatal visits and heavier infants. Rosenzweig and Schultz (1983) address the gestational age issue by predicting an average birthweight according to gestational and then regressing the difference between the average birthweight and the infant's actual birthweight given their gestational age. Performing a similar analysis was not possible in our paper since it is difficult to interpret information on the birth certificate regarding gestational age. However, this should not lead to bias since our estimation technique controls for this type of endogeneity.

addressed within a fertility-control model (Willis, 1973). A household is assumed to decide whether to have an additional child over time based on the effective excess demand for children at given prices, wealth constraints, preferences, and household production of substitutes and compliments for children. If the expected net benefit of an additional child is negative, then the household will practice fertility control in order to reduce the probability of birth, i.e., abortion is considered a means of fertility control. The probability of birth is, therefore, a function of household income, preferences, the opportunity cost of an additional child, and the full costs of contraception and abortion services, etc.[4]

Vector X_i of equation (1) includes information on the pregnant woman such as marital status, age, and race. X_i also includes county-level measures of abortion availability, family planning availability, education, female employment opportunities, religious affiliation, urbanization, poverty, and income.[5] The birth certificate reports the mother's education level, although this information is unavailable for women who abort their pregnancies. Therefore, equation (1) includes the percent of county residents who graduated high school as a proxy for education. Also, the religious affiliation of the mother is unavailable; instead, county percentages of Catholics and Baptists are used.

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[4] For a survey of the literature on abortion demand and a more complete theoretical discussion, see Brown, Jewell, and Rous (2001).

[5] The Alan Guttmacher Institute provides the county of location for abortion providers from a periodic survey of all identified providers in the US, including hospitals, clinics, and physician offices where abortions are performed. The most relevant data available are for 1992 and, therefore, marginal changes in the number or location of abortion providers may have occurred during 1993. The relatively few counties with abortion providers (19 of the 254 counties) allow for calculating the travel distances to acquire an abortion for residents in each county. Travel distance to abortion services is proxied by the road miles traveled from the center of each woman's county of residence to the nearest city with abortion services. The Texas Department of Health, Bureau of Women and Children provides the number of family planning clinics in each county. County-level variations in these services are notably less than for abortion providers. The average Texas county has 2.2 family planning clinics. Since nearly all women reside in counties with family planning services, travel distances are difficult to calculate in the same manner as for abortion providers; furthermore, there would be little variation in travel distances across counties. Instead, the ratio of the number of family planning clinics per 1,000 women ages 20-44 in each county is used to proxy availability costs.

Prenatal Care Equation

Equation (2) models the amount of prenatal care the woman obtains; thus, equation (2) is a demand equation for prenatal care. Prenatal care demand is specified as:

$$(2)\qquad (N_i \,|T_i = 1) = \alpha_2 + \beta_2 Y_i + \varepsilon_2$$

where the dependent variable is a continuous measure of prenatal care, N_i, that mother *i* obtains. Y_i is a vector of explanatory variables that determine the amount of prenatal care a woman desires. α_2 and β_2 represent a set of regression parameters to be estimated. This equation will only be estimated if the woman does not obtain an abortion. ε_2 is the error term.

Since equation (2) is a demand equation for prenatal care, the vector Y_i contains information on the mother including age, number of previous births, marital status, age, education, pre-pregnancy weight, and race. Y_i also includes county-level measures of urbanization, doctor availability, female employment opportunities, urbanization, income, and poverty. Most of these variables are included to measure the woman's preferences. Variables such as marital status, age, education, female employment, income and poverty may pick up the likelihood that the woman has health insurance, and other variables such as urbanization and doctor availability may pick up access to prenatal care. A mother's pre-pregnancy weight may partly measure the mother's (unobserved) health and indirectly her fetus' health.

Birthweight Equation

Equation (3) of the model is a birthweight production function of the following form:

$$(3)\qquad (B_i \,|T_i=1) = \alpha_3 + \beta_3 Z_i + \varepsilon_3$$

where the dependent variable is the birthweight of mother *i*'s infant, B_i, and Z_i is a vector of explanatory variables, including prenatal care usage. α_3 and β_3 represent a set of regression parameters to be estimated. This equation will only be estimated if the woman does not obtain an abortion. e_3 is the error term.

The birthweight production function relates the health outcome, i.e., birthweight, to health inputs. The vector Z_i contains information on the mother including age, number of previous births, education, pre-pregnancy weight, weight gain during pregnancy, cigarettes smoked, alcohol beverages consumed, and race. Z_i also includes the number of prenatal care visits, the gender of the child, and county-level measures of income and poverty. In addition, Z_i contains squared terms of relevant variables, as well as interaction terms between prenatal care use and other explanatory variables.

Discrete Factor Analysis

To remove the unobserved heterogeneity biases, we employ Discrete Factor Analysis, an estimation technique similar to one described in Heckman and Singer (1984), Akin and Rous (1997), and Mroz (1999). Because the technique is full-information maximum likelihood, the three equations in the statistical model are estimated jointly and each individual's contribution to the likelihood function comprise the product of the probability of observing each of the three outcomes – pregnancy resolution, prenatal care, and birthweight. Discrete Factor Analysis is similar to standard full-information maximum likelihood, but instead of making a multivariate parametric assumption about the error term, a discrete semi-parametric distribution that approximates the true distribution of the unobserved variables that are responsible for the correlation between the error terms is estimated. Mroz (1999) demonstrates that the Discrete Factor estimators perform relatively well compared to estimators that assume the correlation between the error terms is normal when the true underlying distribution of the correlation of the error terms is also normal. Discrete Factor estimators also perform better than normal-based estimators when the underlying distribution of the unobserved variables is non-normal.

To facilitate this estimation technique, we expand the error terms and assume the following mixed error structure for each equation.

(4) $\varepsilon_{ji} = \omega_j + \nu_{ji}$

In equation (4), *i* denotes an individual, *j* denotes the equation (1 = pregnancy resolution, 2 = prenatal care visits, and 3 = birthweight), ε_{ji} is each equation's disturbance term, ω_j are the unobserved individual-level factors that help determine the outcome, and ν_{ji} is the portion of each disturbance term that is independent across outcomes. The individual factors, ω_j, are allowed to be correlated across equations. Using Discrete Factor Analysis, a joint discrete multivariate distribution for the factors is estimated. The discrete distribution is made up of the ω_j and corresponding probability weights, all of which are estimated with the remaining parameters of the model. This error term correlation controls for any unobserved heterogeneity including sample selection and endogeneity. The ν_{ji} for the discrete (pregnancy resolution) outcome are distributed logistically, while the ν_{ji} for the continuous outcomes (prenatal care visits and birthweight) are distributed normally, and all ν_{ji} are independent.[6]

III. RESULTS

Since we are most concerned with the effect of prenatal care on birthweight, we concentrate on the results of estimating equation (3). Table Two reports two sets of results for equation (3); the results from equations (1) and (2) are listed in Appendixes B and C. The first set of results (under the heading "Naï ve Model") is from a single equation regression of birthweight on relevant independent variables. The Naï ve Model assumes that no sample-

[6] The parameters in the model are identified due to the nonlinear functional form of the equations. The model gains further identification because each equation contains contemporaneous exclusion restrictions.

selection can be attributed to the pregnancy-resolution decision and that prenatal care is exogenous. The second set of results (under the heading "FIML Model") is from the three-equation, full-information maximum likelihood model using Discrete Factor Analysis, which controls for sample selection and unobserved heterogeneity.

{INSERT TABLE TWO}

Turning first to the coefficients on prenatal care, we find that with both models another prenatal care visit increases birthweight at a decreasing rate.[7] The marginal effect of another visit based on the Naï ve Model is 54.436 – 2*0.889*_prenatal care_, while the marginal effect based on the FIML model is 37.195 – 2*0.288*_prenatal care_. Table One reports that the mean of prenatal care is approximately 11 visits, implying that the marginal effect in the Naï ve Model is 34.878, while the marginal effect in the FIML Model is 30.859. Thus, a woman with the mean number of visits will see an increase of 30 to 34 grams in the birthweight of her child with another prenatal care visit. Given that one ounce is 28.375 grams, this effect is relatively small, implying that prenatal care visits might be less important to infant health than commonly believed. In addition, the result does not seem to be affected much by assumptions concerning the pregnancy-resolution decision and the endogeneity of prenatal care. Thus, it appears that controlling for sample-selection and endogeneity is unnecessary, and a single equation may do an adequate job of showing the relationship between prenatal care use and birthweight.

However, looking only at the marginal effect at the mean can be misleading. In fact, we may be more concerned about women who either have relatively few or many prenatal care visits, since these women are most likely to be affected by sample-selection and endogeneity. It is important, therefore, to analyze the effect of prenatal care on birthweight at different levels of

[7] The squared term on prenatal care from the FIML Model is insignificant; however, the linear and squared terms are jointly significant.

prenatal care. We simulate the effect on birthweight by varying the level of prenatal care from zero to 50 visits, since 49 is the maximum in our sample. We produce the simulations by taking each woman's number of visits, predicting birthweight for each child, and then obtaining a sample average. The results are shown in Figure One. The Naï ve Model predicts an inverted U-shaped birthweight production function, while the production function predicted by the FIML Model is continually increasing, although at a slightly decreasing rate.[8] Below the mean number of visits, the Naï ve Model seems to slightly overestimate the total benefit of prenatal visits, perhaps because women who make fewer visits are healthier and/or have healthier fetuses and they know it.[9] This overestimation could also indicate "positive fetal selection" meaning women who choose to carry their fetuses to term may have healthier babies.

The distinction between the two models becomes most evident at visits above the mean. From the Naï ve Model, additional visits past approximately 20 lead to increasingly lower birthweight, indicating a negative marginal benefit of prenatal care visits. This result could be driven by the endogeneity bias resulting from mothers with less healthy fetuses making more prenatal care visits. Specifically, we may be observing the "adverse selection" in prenatal care found in other studies. In contrast, the FIML Model predicts a positive effect of prenatal care for all visits up to 50. Thus, controlling for endogeneity and sample-selection is important in determining the actual marginal benefit, as measured by increased birthweight, of prenatal care.

{INSERT FIGURE ONE}

Turning next to the other coefficients, most have the expected sign, which is consistent

[8] Our finding from the Naï ve Model is similar to the relationship between prenatal care visits and low-birthweight rates found by Kotelchuck (1994b): Women with many visits and those with few visits both have higher rates of low birthweight than other women.

[9] For the first visit, where the predicted marginal benefit is largest, the FIML model predicts a 36.6 gram increase in birthweight while failing to control for unobserved heterogeneity biases leads to a prediction that the first visit would increase birthweight by 52.7 grams.

across the two models. Women who are older and who have had more children have heavier babies. Women who have less than a high school education have heavier babies. Women who are heavier before pregnancy and who have gained more weight during pregnancy have heavier babies, validating the assumption that mother's weight is an important determinant fetal health. Cigarette smoking has a negative effect on birthweight, while drinking alcohol does not appear to have much effect on birthweight. Both Hispanic and Black women have lighter babies, although much of the effect is eliminated in the FIML Model.

In addition to the variables discussed above, the unobserved heterogeneity parameters are of interest. These parameters result from the estimation of a discrete approximation of the distribution of unobserved factors that are correlated with the error terms in each equation. The parameters that make up this distribution can be found in Appendix D. We were able to identify twenty different types of individuals by unobserved characteristics affecting each of the three outcomes estimated. Since we are only identifying a distribution of unobservables, it is impossible to connect any identified heterogeneity type with specific individuals. What we can say is that each individual in the estimation is predicted to have a 9.0 percent probability of being type 1, a 0.18 percent probability of being type 2, a 1.33 percent probability of being type 3, etc. The ω_j associated with each type and equation tells us how much should be added to the constant coefficient in order to determine what effect having that unobserved characteristic has on the outcome. We find that 42 of the 57 estimated heterogeneity parameters are statistically significant at the 95% level. Additionally, a likelihood-ratio test tests the null hypothesis that all unobserved heterogeneity parameters are equal to zero. This test has a chi-square test statistic of 9172.42, which allows us to strongly reject the null hypothesis at any realistic level of significance. These results confirm the importance of correcting for the potential unobserved heterogeneity biases caused by sample-selection and endogeneity in this model. In addition, since the factors responsible for the error term correlation are by definition unobserved, any attempt to interpret these coefficients would be guesswork.

The married coefficient in the pregnancy-resolution equation (reported in Appendix B) warrants some discussion at this point. The large coefficient (94.161) seems to indicate that married women will always carry their fetuses to term. However, this is not necessarily the case. Looking at the estimated error term correlation distribution, we see that each woman has a 6.86 percent probability of having unobservables that match unobserved heterogeneity type 7 and a 4.25 percent probability of having unobservables that match unobserved heterogeneity type 11. Combining either the seventh or eleventh mass points (with values of -102.000 and -109.999, respectively) with the estimated coefficients of married women in the sample would generate realistic probabilities that even a married woman might not carry her fetus to term. This means that only 11.11 percent of married women would consider abortion, which seems reasonable since most abortions result from unplanned pregnancies and a married woman is much more likely to plan her pregnancy.

IV. CONCLUSION

The Texas data used in this paper offer a unique opportunity to estimate birthweight equations for a diverse group of women from a large geographical region. Our estimates using Discrete Factor Analysis highlight the importance of correcting for the potential unobserved heterogeneity biases. Namely, we find that controlling for sample-selection and endogeneity is important in determining the actual marginal impact of a prenatal care visit on birthweight. Similar to past studies, we show that estimates ignoring unobserved heterogeneity understate the marginal benefit of prenatal care for women who have more visits. This can be viewed as evidence that both “adverse selection” in prenatal care visits and “positive fetal selection” occur in our sample.

Unfortunately, the factors responsible for the error term correlation are unobserved so that the reasons for these differences cannot be estimated. However, we can speculate about these correlations. For instance, women with inferior health endowments may expect lower birthweights and thereby seek more prenatal care during their pregnancies. In this case, overlooking the endogeneity could underestimate the positive impact of prenatal care on birthweight. Moreover, the underestimation would presumably be greater for women who use prenatal care the most (i.e., those with the most inferior health endowments), which is suggested in our simulations. Finally, our estimates indicate that the sample-selection surrounding the pregnancy-resolution decision has a less important influence on birthweight. Thus, the decision of women to give birth may not be highly correlated with healthy behavior and birth outcomes.

Table One
Summary Statistics
n = 37,116

VARIABLE	MEAN	STANDARD DEVIATION
Pregnancy resolution	0.754	0.431
Birthweight	3360.339	563.139
Prenatal care[a]	11.439	4.176
Previous births[a,c]	1.137	1.196
Married[b,c]	0.733	0.442
Age[a,b,c]	27.560	5.362
Education < 9 years[a,c]	0.081	0.272
Education = 12 years[a,c]	0.350	0.477
Education > 12 years[a,c]	0.421	0.494
High school education[b]	72.310	9.641
Travel distance[b]	31.496	36.067
Family planning[b]	0.904	1.744
Obstetrician/gynecologist[c]	0.409	0.791
Female employment[b,c]	57.291	7.247
Catholic[b]	22.561	21.034
Baptist[b]	17.495	9.515
Urbanization[b,c]	83.972	21.304
Weight[a,c]	143.456	32.680
Weight gain[a]	30.658	12.711
Male[a]	0.508	0.500
Cigarettes[a]	1.051	4.105
Drinks[a]	0.031	0.735
Hispanic[a,b,c]	0.322	0.467
Black[a,b,c]	0.148	0.355
Poverty[a,b,c]	19.838	12.982
Income[a,b,c]	27.862	6.009

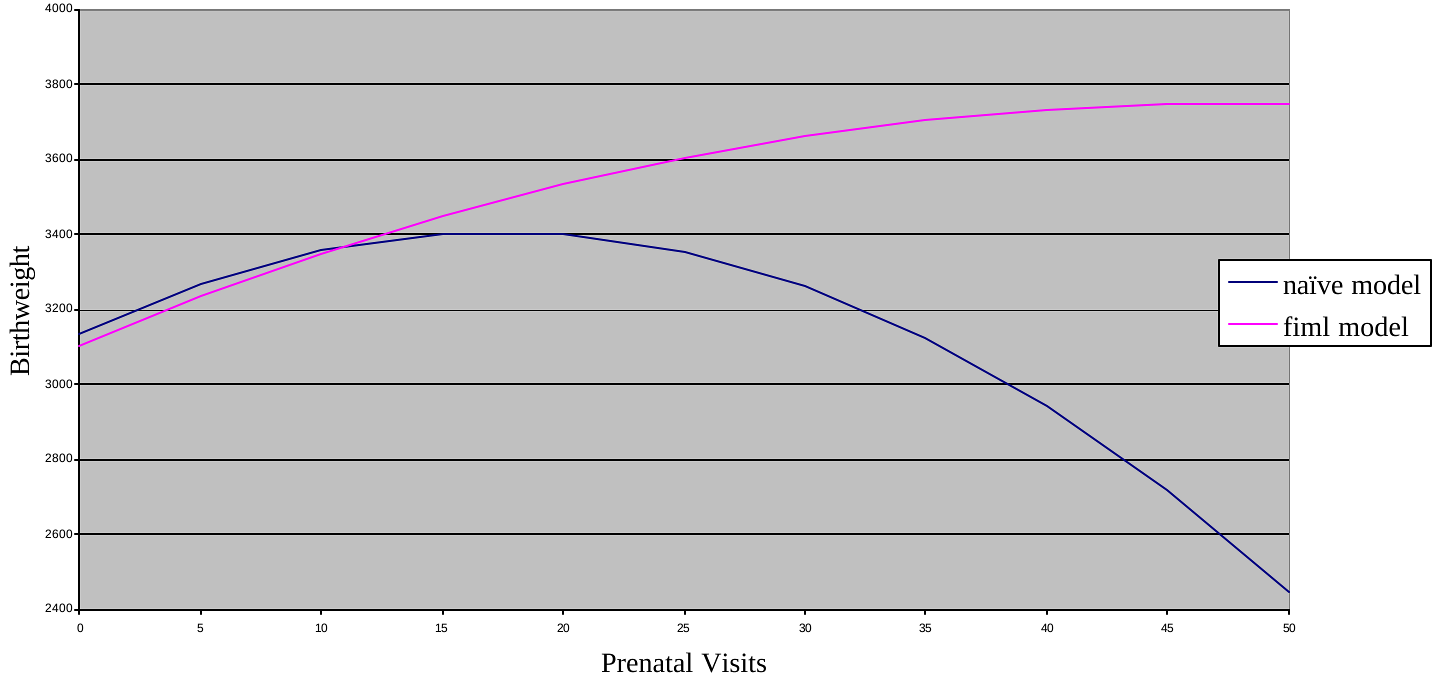
[a] Included in birthweight equation (Table Two)
[b] Included in pregnancy-resolution equation (Appendix B)
[c] Included in prenatal care equation (Appendix C)

Table Two
Birthweight Equation
n = 37,116
(absolute value of t-score in parentesis)

VARIABLE	NAÏ VE MODEL	FIML MODEL
Constant	1085.951 (7.799)	1299.019 (8.820)
Prenatal care	54.436 (6.592)	37.195 (2.862)
Prenatal care squared	-0.899 (12.65)	-0.288 (0.685)
Previous births	93.927 (10.93)	69.870 (8.047)
Previous births squared	-7.492 (7.304)	-5.785 (6.293)
Age	10.085 (1.881)	7.060 (1.403)
Age squared	-0.268 (2.979)	-0.157 (1.908)
Education < 9 years	147.300 (5.194)	132.962 (4.789)
Education = 12 years	5.073 (0.223)	-3.810 (0.164)
Education > 12 years	21.748 (0.824)	21.447 (0.773)
Weight	8.297 (15.25)	8.592 (17.359)
Weight squared	-0.013 (8.372)	-0.013 (9.373)
Weight gain	20.339 (22.57)	15.423 (18.25)
Weight gain squared	-0.113 (11.03)	-0.065 (6.946)
Male	88.366 (5.570)	101.985 (6.789)
Cigarettes	-18.368 (7.661)	-20.757 (9.118)
Cigarettes squared	0.273 (4.494)	0.339 (5.034)
Drinks	-9.460 (0.608)	13.541 (0.926)
Drinks squared	0.162 (1.297)	0.009 (0.080)
Hispanic	-113.129 (2.018)	-14.997 (0.281)

Black	-429.552 (6.721)	-213.077 (3.508)
Poverty	12.954 (4.582)	5.576 (2.033)
Poverty squared	-0.059 (2.453)	-0.030 (1.405)
Income	14.495 (3.682)	10.596 (2.944)
Income squared	-0.081 (1.466)	-0.112 (2.301)
*Prenatal care * live births*	-2.113 (3.554)	-0.537 (0.884)
*Prenatal care * cigarettes*	-0.105 (0.684)	-0.021 (0.142)
*Prenatal care * drinks*	-1.043 (0.819)	-2.577 (1.976)
*Prenatal care * age*	0.306 (2.147)	0.077 (0.524)
*Prenatal care * weight*	-0.027 (1.388)	-0.036 (1.904)
*Prenatal care * weight gain*	-0.314 (6.294)	-0.178 (3.719)
*Prenatal care * poverty*	-0.532 (3.248)	-0.116 (0.709)
*Prenatal care * income*	-0.384 (2.083)	0.014 (0.081)
*Prenatal care * education < 9*	-5.794 (2.189)	-3.597 (1.420)
*Prenatal care * education = 12*	0.489 (0.246)	-0.142 (0.071)
*Prenatal care * education > 12*	1.482 (0.664)	0.288 (0.125)
*Prenatal care * male*	1.956 (1.501)	1.580 (1.287)
*Prenatal care * hispanic*	5.984 (1.594)	0.155 (0.043)
*Prenatal care * black*	17.725 (4.321)	3.759 (0.952)
*Weight gain * hispanic*	-0.550 (2.804)	-0.589 (3.316)
*Weight gain * black*	-0.910 (3.868)	-0.880 (4.134)

Figure 1
Predicted Birthweight



Appendix A
Data Description and Sources

VARIABLE	DESCRIPTION	SOURCE
Pregnancy resolution	1993 individual data: 1 if birth, 0 if abortion	Abortion or Birth Certificate Texas Department of Health
Birthweight	1993 individual data: child's birthweight in grams	Birth Certificate Texas Department of Health
Prenatal care	1993 individual data: number of prenatal care visits	Birth Certificate Texas Department of Health
Previous births	1993 individual data: number of previous live births	Abortion or Birth Certificate Texas Department of Health
Married	1993 individual data: mother's marital status at pregnancy resolution, 1 if married, 0 if not	Abortion or Birth Certificate Texas Department of Health
Age	1993 individual data: mother's age at pregnancy resolution	Abortion or Birth Certificate Texas Department of Health
Education < 9 years	1993 individual data: mother's education less than 9 years	Birth Certificate Texas Department of Health
Education = 12 years	1993 individual data: mother's education 12 years	Birth Certificate Texas Department of Health
Education > 12 years	1993 individual data: mother's education more than 12 years	Birth Certificate Texas Department of Health
High school education	1990 county data: percent of population who graduated from high school	Murdock and Hoque (1992)
Travel distance	1992 county data: miles from county of residence to nearest city with an abortion provider	The Alan Guttmacher Institute
Family planning	1993 county data: number of family planning clinics per 1,000 women age 20-44	Bureau of Women and Children Texas Department of Health
Obstetrician/gynecologist	1993 county data: number of OB/GYN medical doctors per 1,000 women age 20-44	Bureau of Women and Children Texas Department of Health
Female employment	1990 county data: percent of female population employed	Murdock and Hoque (1992)
Catholic	1990 county data: percent of population who identify with catholic church	Bradley et al. (1992)

Baptist	1990 county data: percent of population who identify with baptist church	Bradley et al. (1992)
Urbanization	1990 county data: percent of population in urbanized area	Murdock and Hoque (1992)
Weight	1993 individual data: mother's weight in pounds after birth	Birth Certificate Texas Department of Health
Weight gain	1993 individual data: mother's weight gain in pounds during pregnancy	Birth Certificate Texas Department of Health
Male	1993 individual data: child's gender, 1 if male, 0 if female	Birth Certificate Texas Department of Health
Cigarettes	1993 individual data: number of cigarettes smoked per day while pregnant	Birth Certificate Texas Department of Health
Drinks	1993 individual data: number of alcohol beverages consumed per day while pregnant	Birth Certificate Texas Department of Health
Hispanic	1993 individual data: mother of mexican-hispanic heritage	Abortion or Birth Certificate Texas Department of Health
Black	1993 individual data: mother of african-american heritage	Abortion or Birth Certificate Texas Department of Health
Poverty	1990 county data: percent of county population below poverty line (race specific)	Murdock and Hoque (1992)
Income	1990 county data: median household income in county, measured in 1,000s	Murdock and Hoque (1992)

Appendix B
Pregnancy-Resolution Equation
Dependent Variable = 1 if gave birth, 0 if abortion
n = 49,209
(absolute value of t-score in parentesis)

VARIABLE	FIML MODEL
Constant	18.378 (5.214)
Married	94.161 (76.353)
Age	-0.062 (0.473)
Age squared	-0.00119 (0.529)
High school education	-0.040 (1.408)
Travel distance	0.024 (6.120)
Family planning	-0.273 (4.223)
Female employment	-0.252 (6.217)
Catholic	0.008 (0.852)
Baptist	0.071 (4.393)
Urbanization	-0.008 (1.214)
Hispanic	1.661 (2.661)
Black	1.942 (2.804)
Poverty	0.069 (2.308)
Income	0.152 (4.455)

Appendix C
Prenatal Care Equation
n = 37,116
(absolute value of t-score in parentesis)

VARIABLE	FIML MODEL
Constant	7.396 (10.952)
Previous births	-0.324 (18.394)
Married	1.722 (15.273)
Age	0.255 (7.496)
Age squared	-0.00329 (5.710)
Education < 9 years	-0.731 (8.475)
Education = 12 years	0.576 (9.604)
Education > 12 years	0.854 (13.331)
Obstetrician/gynecologist	-0.034 (1.718)
Female employment	-0.006 (0.959)
Urbanization	0.001 (0.948)
Weight	0.011 (3.343)
Weight squared	-0.00002 (1.645)
Hispanic	0.415 (3.776)
Black	0.286 (2.411)
Poverty	-0.042 (8.887)
Income	-0.018 (2.868)

Appendix D
Estimated Unobserved Heterogeneity Distribution Parameters
(absolute value of t-scores in parentheses)

Mass Point	Probability Weights	Pregnancy Resolution (w_1)	Prenatal Care Visits (w_2)	Birth Weight (w_3)
1	*0.0900*	*0*	*0*	*0*
2	*0.0018*	*-1.308* *(0.450)*	*-1.135* *(1.011)*	*-2045.575* *(19.009)*
3	*0.0133*	*-4.466* *(3.010)*	*-4.471* *(10.159)*	*-1152.581* *(14.792)*
4	*0.0004*	*-30.910* *(15.463)*	*13.730* *(17.267)*	*-1832.533* *(9.170)*
5	*0.0277*	*-4.360* *(3.074)*	*-10.234* *(29.560)*	*390.023* *(4.849)*
6	*0.0020*	*-6.172* *(3.552)*	*16.352* *(32.157)*	*-277.630* *(1.658)*
7	*0.0686*	*-102.000* *(128.746)*	*-7.735* *(18.435)*	*128.642* *(2.038)*
8	*0.4321*	*-13.324* *(7.490)*	*-1.903* *(5.621)*	*84.403* *(2.299)*
9	*0.0002*	*13.379* *(2.733)*	*32.556* *(39.054)*	*-767.760* *(1.511)*
10	*0.0126*	*-30.468* *(5.919)*	*-0.0003* *(0.001)*	*-1051.600* *(13.922)*
11	*0.0425*	*-109.999* *(97.600)*	*8.950* *(2.036)*	*67.404* *(0.565)*
12	*0.0007*	*-49.371* *(5.942)*	*24.339* *(37.137)*	*-359.183* *(1.238)*
13	*0.0844*	*-7.220* *(4.716)*	*-4.785* *(8.392)*	*217.464* *(2.998)*
14	*0.0042*	*-5.879* *(3.625)*	*-8.079* *(17.691)*	*-2009.344* *(27.183)*
15	*0.0033*	*10.035* *(1.605)*	*4.642* *(8.757)*	*-1304.498* *(8.429)*
16	*0.0051*	*0.350* *(0.084)*	*10.204* *(22.204)*	*-263.788* *(3.038)*
17	*0.0058*	*-2.877* *(1.554)*	*-9.953* *(22.448)*	*-589.737* *(4.840)*
18	*0.0417*	*-4.099* *(2.908)*	*4.543* *(13.511)*	*-90.432* *(1.508)*
19	*0.1172*	*-5.100* *(4.879)*	*-0.203* *(0.326)*	*80.116* *(1.080)*
20	*0.0463*	*-1.599* *(1.013)*	*-5.397* *(16.086)*	*49.484* *(0.789)*

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