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The effects of Medicaid and maternal depression on prenatal care and infant health

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THE EFFECTS OF MEDICAID AND MATERNAL DEPRESSION ON PRENATAL CARE AND INFANT HEALTH

BY

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DEDICATION

This dissertation is dedicated in memory of Mr. Jeffrey Spring. He was a truly inspirational teacher who taught me that the most challenging of disciplines are also the most enjoyable and rewarding.

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Abstract

The Effects of Medicaid and Maternal Depression on Prenatal Care and Infant Health

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While in recent years, the infant health production function literature has expanded to incorporate behavioral inputs into the production of infant health current research fails to incorporate the Medicaid-private insurance choice into the mother's decision making process. This dissertation seeks to address this by treating private insurance and Medicaid as endogenous while considering the effects that the Medicaid eligibility rules have on both kinds of coverage. Medicaid and private insurance are entered directly into the health production function so that quality effects may be captured. In addition, a woman's state of mental health is also incorporated into the health production process. Depression may have direct and indirect effects on infant health, as it is a potential negative input into the production process but also a factor that may influence the choice and productivity of other inputs (such as prenatal care).

A traditional infant health production model is extended to include the Medicaid-private insurance choice and guides the formulation of the two-stage empirical model. Two reduced form, univariate probits are estimated in the first stage on the Medicaid-private insurance choice. Then, a treatment effects model simultaneously estimates the interaction between prenatal care and birth weight as well as the effects of depression, Medicaid, and private insurance. Finally, utilizing the parameters estimated with my original (1988) data, the effects of expanding Medicaid eligibility according to the 1997 rules are simulated. Additionally, a similar simulation predicts the effect of mechanically "treating" depressed women or reducing their depressive symptoms (by lowering their CES-D depression score) on the key variables.

Results indicate that both depression and Medicaid participation lead to a reduction in birth weight. Prenatal care has no significant effect on birth weight but both smoking and anthropometry do. Simulations reveal that expanding Medicaid eligibility is predicted to improve health outcomes particularly for low-income women and black women. Treating depressed women is also predicted to increase birth weights.

CHAPTER I

INTRODUCTION

General framework, central issues, and contribution

Understanding the correlates of infant health has become an issue of great importance in the U.S. since we have learned that it has tremendous implications for childhood and adolescent health and well being. Some aspects of infant health have improved over the past decade. Infant mortality rates for white children have fallen from 8.4 deaths per thousand in 1988 to 6.3 deaths per thousand in 1995. For black children, the rate has also fallen from 18.5 to 15.1 deaths over the same time period. However, not every infant health indicator is showing favorable trends. The incidence of low birth weight infants (birth weights of less than 2500 grams or 5.5 pounds) is on the rise for white infants from 5.7% of all white births in 1988 to 6.3% in 1995. For blacks, however, the rate has fallen from 13.3% of all black births to 13.0%[1]. These statistics suggest two paths of important research that need to be addressed. The first is to better understand the correlates of birth weight and low birth weight, as these are two important indicators of infant health. The second is to determine how these correlates differ by race and why the incidence of low birth weight is rising for whites. The statistics shown above yield evidence that the incidence of low birth weight, although falling, is higher for blacks than it is for whites.

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[1] Statistics available from http://www.childstats.gov

The analytical tools used in economics are useful and appropriate to evaluate the factors that are correlated with infant health outcomes. In fact, Rosenzweig and Schultz's 1982 paper "The Behavior of Mothers as Inputs to Child Health: The Determinants of Birth Weight, Gestation, and Rate of Fetal Growth" has inspired a branch of literature on the infant health production function. This literature takes the approach that infant health or birth weight is the outcome of a production process called pregnancy. In recent years, the importance of incorporating behavioral inputs, primarily maternal behavior such as smoking and prenatal care, has been recognized by this literature. Many studies (including Rosenzweig and Schultz) have found that these inputs significantly affect birth weight.

At the same time, several studies have investigated the decision to participate in Medicaid and how that decision affects private insurance coverage. Crowding out rates have been estimated as high as 50% in some studies. In addition, other studies have evaluated the effects of Medicaid and private insurance on infant health outcomes. However, current research fails to incorporate the Medicaid-private insurance choice into the mother's decisions regarding the health of her infant. That is, insurance choice has not been explicitly modeled as a choice input into the production of infant health. This leaves open the question of how Medicaid versus private insurance influences the mother's decision to seek prenatal care and, ultimately, the health of her infant.

Studies devoted toward understanding the effects of depression have also been on the forefront of health economics research. Studies such as Broadhead et al. (1990) indicate that depressed individuals function poorer on a daily basis, missing more days of

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[1] Statistics available from http://www.childstats.gov

work and school, than non-depressed individuals. In addition, other research (such as Dawson et al., 1997a) indicates that depressed mothers pass on their "depressed state" to their infants in the form of reduced brain activity. The infant health production literature has neglected to incorporate a woman's state of mental health as an input that enters into the infant health production process. Depression may have direct and indirect effects on infant health, as it is a potential negative input into the production process but also a factor that may influence the choice of other inputs (such as prenatal care) and the productivity of those inputs.

This dissertation seeks to answer these questions and, in so doing, expands upon these bodies of literature in a number of important ways. First, private insurance and Medicaid are treated as endogenous or choice inputs in the production of infant health. I assume that a woman chooses the type of insurance coverage that maximizes her own utility, which is a function of infant health. In addition, the effects of the Medicaid eligibility rules on both kinds of coverage are considered. It is expected that the Medicaid income eligibility rules influence the type of insurance coverage demanded. Second, Medicaid income eligibility has expanded tremendously during the past decade. Many women and children who were not eligible to receive Medicaid in the mid-1980s are now eligible. This provides the opportunity to simulate how these expansions affect the choice to participate in Medicaid and purchase private insurance. More importantly, it can be determined how these expansions affect the demand for prenatal care, and ultimately, how they affect infant health. Finally, I incorporate a woman's state of mental health or severity of depression into the health production process. In light of the depression literature, it is expected that a depressed woman may demand a sub-optimal

quantity of prenatal care, affecting the health of her infant. Additionally, whether depression directly affects infant health in the form of birth weight can also be determined. The direct and indirect effects of treating (or curing) depression in a sample of pregnant women through the use of a policy simulation can shed light on whether it is an effective tool in improving outcomes.

Disentangling these issues requires that I first extend the traditional infant health production model to include the Medicaid-private insurance choice. This theoretical framework guides the formulation of my two-stage empirical model. The first stage estimates a reduced-form, Medicaid-private insurance choice with two univariate probits. I then use a treatment effects model to recursively estimate the interaction between prenatal care (an input into the production process) and birth weight (the health outcome), as well as the effects of depression, Medicaid and private insurance. My model reveals the complex effects that expanding Medicaid eligibility may have on infant health. In addition, the entire model is stratified by race, specifically, by black and white women. Stratification allows both the intercept and all of the parameters to vary according to whether the mother is black or white. Utilizing the parameters estimated with the original (1988) data, I simulate the effects of expanding Medicaid eligibility according to the 1997 rules and the effects of reducing depressive symptoms in a sample of depressed women.

Structure of following chapters

The health production function literature is well established and is reviewed in greater detail in **Chapter II**. A number of extensions have been made to the infant health production framework developed by Rosenzweig and Schultz (1982). One extension

made by Warner (1995,1998) is the inclusion of anthropometric characteristics or characteristics that define the mother's physical structure such as height and her own birth weight, into the health production function. It is believed that these characteristics are linked to birth weight. Another extension made by Grossman and Joyce (1990) is the development of a correction statistic that controls for the self-selection that occurs when evaluating a subset of the pregnant population, specifically, pregnancies that result in a live birth. The premise behind this correction is that women who continue a pregnancy to term are more likely healthier and care more for their pregnancy than women whose pregnancy ends in miscarriage or abortion, thus biasing parameter estimates. If the latter group of women had continued their pregnancy to full term, they likely would have demanded less than adequate prenatal care in addition to bearing a child of lower birth weight. Another class of extensions incorporates health insurance coverage as a choice or endogenous variable. Moffitt (1983), Cutler and Gruber (1996), Currie and Gruber (1996), and Joyce (1997) all to some extent recognize that insurance and Medicaid are endogenous and model it that way. Since the "quality" effect of Medicaid is at question here in terms of its effect on birth weight, a brief discussion entailing the overwhelming shift toward Medicaid managed care is discussed. While Medicaid managed care may have significant implications for the outcomes of the model the transition to managed care it is not directly modeled here. The data are not rich enough to support such an analysis since the data are collected in 1988, before the rise in managed care. Finally, the epidemiological literature pertaining to depression and prenatal care is also discussed. This literature indicates a link between depression, infant health, and individual functioning.

The theoretical and empirical models are derived in **Chapter III.** These models jointly estimate the interaction between depression, prenatal care (the primary input into the production of infant health), and birth weight (a commonly used indicator of infant health), highlighting the effect that insurance coverage has on the system. The basic theoretical framework comes from Rosenzweig and Schultz (1982). They utilize a utility maximizing approach to develop a model of infant health production. The incorporation of a Medicaid or welfare stigma into the framework comes from Moffitt (1983). This insurance "choice" is embedded with the budget constraint associated with the utility function. The theoretical model predicts the type of insurance coverage (Medicaid, private insurance, or no insurance) that maximizes the woman's utility.

The empirical model is an extension of many of the papers discussed in the literature review. The primary data set used is quite rich and includes data on a sample of roughly 26,000 women who experienced a live birth, fetal death, or infant death in 1988. Once outliers and fetal and infant deaths were removed and the data was stratified by race, the sample used in the analysis includes 2562 white women and 2106 black women. Several statistical, sample-selection issues are addressed prior to the model estimation. The first issue addresses "live birth" sample selection where only pregnancies that ended in a live birth are included in the overall analysis. Another discusses endogenizing insurance choice.

The primary model estimated is a two-stage, recursive treatment effects model. Medicaid and insurance are estimated in the first stage in order to produce inverse Mills ratios that control for sample selection. The final stage simultaneously estimates prenatal care demand and birth weight. The onset of prenatal care and the number of visits

adjusted for gestation are two alternative prenatal care measures defined. Birth weight is defined in four different ways. The first is the actual birth weight in grams. The second is the actual birth weight in grams *only* if gestation is greater than 37 weeks. That is, only full-term births are included. This measure is important since it standardizes gestation for the sample of women, eliminates any pre-term births, and is a better reflection of fetal growth. The third measure is a dummy variable indicating the incidence of low birth weight. Finally, the last measure is the same as the third but limited to term births. Included in the final stage equations are the actual Medicaid and insurance variables plus their associated Mills ratios. These are the "treatment effects". The model evaluates the "treatment effect" of Medicaid and insurance on prenatal care and birth weight. Additionally, depression is also included in both the prenatal care and birth weight equations. Since other studies more commonly use an instrumental variables model to jointly estimate prenatal care and birth weight, this model is also estimated. Finally, for comparison, a birth weight equation that treats all variables as exogenous as well as a reduced-form birth weight equation are estimated.

Chapter IV develops two policy simulations that evaluate a) the impact of expanding Medicaid income eligibility and b) the impact of treating depression in depressed individuals, on the probability of having Medicaid and insurance, prenatal care, and birth weight. The Medicaid income eligibility simulation only evaluates a gross change in the dollar amount threshold (which varies by household size and state). Confounding effects such as the transition from the AFDC program to TANF and Medicaid managed care are not modeled. While they are also important policy shifts that have occurred in the Medicaid program during the past decade, the 1988 NMIHS data

used cannot appropriately capture these effects. Using the Center for Epidemiological Studies Depression scale (CES-D scale) which rates depressive symptoms on a scale of 0 - 60 (60 reflecting the most severe symptoms), the depression simulation evaluates the impact of reducing a woman's score that is greater than 16 (the "depression threshold") to a score of 16. Essentially, censoring the score to 16 is considered "treating depression".

A simulation is an improvement over other studies in the literature since it takes into account both the direct and indirect effects of a policy change. For example, the effect of eligibility is likely to be non-linear in prenatal care and birth weight. Therefore, including eligibility directly in these equations may lead to poor results. One important element to note is that expanding Medicaid eligibility to a new group of women does not directly translate into participation by these women. Several studies have shown that the Medicaid take-up rate, the percentage of Medicaid eligible women who actually participate in Medicaid, is far less than 100%. An important feature of the policy simulation (and a contribution to the literature) is that it does not impose participation on an individual. The simulation only estimates the probability that a woman will participate once she becomes eligible. Using the parameter estimates already obtained from previous estimations, the model uses a woman's characteristics to predict whether she will participate if eligibility rules change. These effects are then simulated on prenatal care and birth weight. A similar process is used in the depression simulation.

Chapter V concludes.

CHAPTER II

LITERATURE REVIEW

Introduction

Infant health is not homogeneous across all births in the US each year. Some infants are born too soon, while others are born too small. Some will live a full life while others may die within the first month or first year of life. The primary goal of the papers in the first major section of this literature review is to try to explain what factors contribute to the variation in infant health. If the variation in infant health is solely due to genetic and immeasurable factors or factors unknown to the researcher then an economic analysis of the problem is not appropriate. However, a considerable amount of economic and epidemiological literature suggests that many other factors contribute to the variation in infant health. Factors such as the onset and amount of prenatal care and the presence of smoking during pregnancy are factors that can be appropriately measured by the researcher in an economic model.

The model that is well established in the literature for evaluating this type of problem is the health production function. The focus of this model is to recognize parental behavior as a primary input into the health production function. Parental behavior can mean anything from fertility behavior (choosing the optimal number and spacing of births) to maternal behaviors such as smoking, substance abuse, and demanding prenatal care. This is not to say that other inputs such as anthropometric

characteristics (such as the mother's height, weight, own birth weight, and race) and other socioeconomic characteristics and demographics are not included. While the existing literature has incorporated a variety of these inputs, in a variety of ways, into the model, there are still essential inputs that have been neglected or that have not been entered into the model appropriately.

This dissertation contributes to the economics literature by extending the existing health production function literature in a number of ways, and at the same time connecting several different bodies of literature. The first contribution is that the Medicaid and welfare literature is used to modify the infant health production model. To date, the household production function literature has not fully incorporated the endogeneity of participating in public programs such as Medicaid on infant health. That is, this dissertation models insurance coverage as a choice where a woman chooses the type of coverage that maximizes her utility. However, Medicaid eligibility rules are measured as an exogenous shock. The second contribution applies this concept to the empirical treatment effects model, disentangling the direct and indirect (through prenatal care) effects of Medicaid on infant health. The empirical section more completely discusses the techniques available to control for these complex relationships. The third contribution is that the epidemiological literature is used to inform the formulation of the health production function by expanding the scope of behavioral inputs to include maternal depression. Epidemiological research has shown that a significant link exists between depression and infant health. Depression may have both direct and indirect effects on infant health, as it is a potential negative input into the production process but also a factor that may influence the choice of other inputs (such as prenatal care) and the

productivity of those inputs. The final contribution is that a policy simulation captures both the direct and indirect effects of the Medicaid eligibility expansions that occurred during the past decade as well as an alternative policy of treating maternal depression.

Health Production Function

Origins of the health production function

The health production function provides the foundation for the framework developed in this dissertation. Grossman (1972) developed the first theoretical formulation of this model. Prior to his contribution, similar models of household production (developed by Becker (1965), Lancaster (1966), and others) focused on time allocation in non-market activities within the household. The primary difference between these earlier models and Grossman's model is that the latter focuses on the *total amount of time* devoted toward market and non-market activities whereas the former focuses on the *allocation* of that time. Put another way, an individual's stock of knowledge or human capital affects her productivity and efficiency in market and non-market activities, thus affecting how she allocates her time. An individual's stock of health affects the total amount of time devoted toward market and non-market activities since poor health reduces the total amount of time available. Assuming that an individual wishes to maximize the amount of time she devotes toward these activities and minimize sick time, the stock of health capital enters directly into the utility function.

According to Grossman, an individual is said to inherit an initial stock of health at birth. This stock depreciates throughout life until the stock reaches a minimum, H_{min}, at which time death occurs. Therefore, throughout one's life, an individual must continually

invest in health capital, via a health production function, in order to delay the inevitable, H_{min}. One primary way to invest in health is to demand medical services. Grossman argues that "what consumers demand when they purchase medical services are not these services, per se but, rather 'good health' (Grossman p. 224). Therefore, the demand for medical services is said to be a derived demand[2]. By demanding medical services one can invest in good health.

The general model proposed is an intertemporal model of utility maximization subject to budget and time constraints. While Grossman's model makes a significant contribution to the health economics literature, two more recent papers by Rosenzweig and Schultz (1982, 1983) provide a more elegant and suitable model of health production. This is one of the models that my dissertation draws heavily upon. A summary of the models from key papers discussed in the literature review can be found in **Table 1**. **Tables 2** and **3** summarize the measures of birth weight and prenatal care found in the following articles.

Health production function: Initial specification of model

The model developed in their papers utilizes a similar approach to Grossman (1972) by embedding a health production function into a utility maximizing framework. Their primary contribution is the recognition that maternal behavior plays a large role in determining child health and thus should be incorporated as inputs into the health production function. Maternal behavior can mean anything from fertility behavior

[2] The story of derived demand is as follows: The demand for an input, medical services, is derived from the demand for the product itself, health or health capital. Thus, if the demand for the product (health) is zero, then the demand for the input (medical services) is also zero. As long as an individual invests in health capital (the product), the demand for medical services (the input) will be positive. At death, when the demand for health is zero, the demand for medical services is also zero.

(choosing the optimal number and spacing of births) to other behaviors such as smoking, substance abuse, and demanding prenatal care. Furthermore, a woman selects the inputs (that enter into the health production function) that maximize her family's utility in addition to ones that reflect her unobserved health endowment. For instance, if a woman believes that she has a poor health endowment, she may demand more healthy inputs to neutralize the effect that her poor health endowment will have on her fetus' health. Clearly, the inclusion of such inputs is significant.

In light of this, the family utility function[3] is defined as the following:

$$1.\ U = U(X, Y, H)$$

where H represents the health of each of the family's children, Y reflects consumer goods that affect health (such as smoking) and, X indicates health-neutral consumer goods. In addition, the health of the infant can be represented by the following health production function:

$$2.\ H = f(Y, Z, \mu)$$

such that Y again reflects the consumer goods that affect health, Z represents infant health enhancement goods that do not directly enhance family utility but do directly enhance infant health (such as medical care), and μ is the health "endowment" passed along to the infant. This endowment may be passed via genetics or may simply indicate environmental conditions that are uninfluenced by the parental unit.

The family maximizes utility given the infant health production function and subject to the budget constraint:

$$3.\ I = XP_X + YP_Y + ZP_Z$$

where I is income and P_X, P_Y, and P_Z are the prices of those goods, respectively. This budget constraint indicates an important feature of the model. Since only the prices of X, Y, and Z appear in the constraint, only these three goods can be purchased directly. Infant health (H) (or birth) cannot be purchased directly. This is consistent with Grossman (1972). Rather, infant health is included since it is a utility augmenting good for which other goods must be sacrificed. That is, in order to increase investment in infant health, one must decrease investment in X and possibly Y.

The Lagrangian formed from this model is the following:[4]

$$\max_{X,Y,Z} L = U(X, Y, f(Y, Z, \mu)) + \lambda(I - XP_X - YP_Y - ZP_Z)$$

from which the following first-order conditions can be derived:

$$4.\ \frac{\partial L}{\partial X} = \frac{\partial U}{\partial X} - \lambda P_X = 0 \Rightarrow \frac{\partial U}{\partial X} = \lambda P_X$$

$$5.\ \frac{\partial L}{\partial Y} = \frac{\partial U}{\partial Y} + \frac{\partial U}{\partial H} \bullet \frac{\partial f}{\partial Y} - \lambda P_Y = 0 \Rightarrow \frac{\partial U}{\partial Y} + \frac{\partial U}{\partial H} \bullet \frac{\partial f}{\partial Y} = \lambda P_Y$$

$$6.\ \frac{\partial L}{\partial Z} = \frac{\partial U}{\partial H} \bullet \frac{\partial f}{\partial Z} - \lambda P_Z = 0 \Rightarrow \frac{\partial U}{\partial H} \bullet \frac{\partial f}{\partial Z} = \lambda P_Z$$

The first-order conditions reveal which variables affect utility directly and which ones affect it indirectly through health. Equation **4** shows that X only affects utility directly and is therefore health-neutral. Equation **5** illustrates that Y not only affects utility

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[3] The theoretical is model taken from the 1982 paper.

directly but also affects utility through health. Equation **6** shows that Z only affects utility through its' effect on health but does not directly affect utility. Finally, the authors derive input demand equations for X, Y, and Z that are a function of all of the exogenous variables in the system:

$$7.\ X = D_X(P_X, P_Y, P_Z, I, \mu)$$

$$8.\ Y = D_Y(P_X, P_Y, P_Z, I, \mu)$$

$$9.\ Z = D_Z(P_X, P_Y, P_Z, I, \mu)$$

In addition to providing a sound theoretical framework to evaluate the production of infant health, Rosenzweig and Schultz recognize the endogeneity bias created by one of the key inputs, Z. That authors state that if this model were empirically estimated using ordinary least-squares (OLS), the estimate of $\frac{\partial f}{\partial Z}$ would be upwardly biased. The reason for this, the authors indicate, is that parents who expect to have healthier babies or live in a clean environment (represented by $\mu>0$) may be observed to demand less of the variable Z yet have healthier children[5]. However, despite μ affecting parental behavior through their demand for Z, μ is not correlated with any input demand prices. Therefore, Rosenzweig and Schultz indicate that it is possible to estimate the model unbiasedly by purging the variation in μ from the variation in Z and Y. Empirically, this requires a two-stage model. The reduced-form input demand equations would be unbiasedly estimated in the first stage. From this, the predicted values of these variables would be included in the structural-form of the infant health production function in the second stage.

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[4] This equation was not explicitly taken from this paper although it was alluded to. Therefore, this equation is not numbered.

The four input demand equations estimated in the first stage (since they are considered endogenous in the second stage infant health production function) are the following: ***AGE*** (mother's age at delivery), ***SMOKING*** (number of cigarettes smoked per day during pregnancy), and ***BIRTHS*** (number of live births the mother experienced including this birth) representing ***Y*** - health related goods that provide direct utility to the mother but also affect child health, and ***DELAY*** (number of months into the pregnancy that woman sought medical care) representing ***Z*** - goods that only affect child health. These four dependent variables are estimated as reduced-from equations and are regressed on the explanatory variables in the system. These include the mother's education, husband's income, several per capita variables that indicate the local hospital and physician environment, state unemployment characteristics, price of cigarettes, population density, mother's race, and year indicators. Neither insurance status nor any additional genetic factors are included as regressors.

[6]Results from the first-stage reduced-form models reveal the following things. White women, with higher family incomes, more education, who live in a metropolitan area, in counties with more public health facilities or with greater government expenditures on health facilities begin the onset of prenatal care (***DELAY***) earlier. Findings also show that white women, with higher family incomes, less education, who live in areas where female unemployment rates are low (1982), and in areas where the per capita number of physicians and availability of family planning services is higher (1982), who live in a metropolitan area (1983), and where the sales tax on cigarettes is lower

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[5] Ceteris paribus, healthy women that demand less visits will have healthier children than unhealthy women that demand less visits. Therefore, birth weight (a measure of infant health) will be higher than it should be.

(1983) smoke more cigarettes (***SMOKING***) during pregnancy. In addition, women with little education and many years of education (i.e. non-linear U-shaped), who live in regions with less female unemployment, near hospitals, with lower family incomes (1983), and in a metropolitan area (1983) tend to have children later (***AGE***). Women that are less educated, with higher family incomes, are black, who live in more rural areas, far from family planning clinics, near more hospitals, and far from areas where industries employ women (1983) are likely to have more children (***BIRTH***).

In the second stage, a structural-form infant health production function is estimated:

10. $H = f(AGE, DELAY, SMOKING, BIRTHS, POPDENSITY, 1967, 1968, BLACK; \mu)$

where health is defined as birth weight and birth weight adjusted for gestation[7]. Health is regressed across Y - health related goods that provide direct utility to the mother but also affect child health (***AGE***, ***SMOKING***, ***BIRTHS***), Z - goods that only affect child health (***DELAY***), and μ - race (indicating genetics) and environmental endowments.

The results in the 1982 and 1983 papers are similar with a few exceptions. However, note that the 1983 paper does not include gestation as a dependent variable. Delay in seeking prenatal care is associated with lower birth weight and shorter gestation, but has no effect on the standardized birth weight while smoking is found to lower birth weight, increase the length of gestation, but lower the standardized birth weight. These

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[6] If no year is indicated, then both the 1982 & 1983 papers showed those results. Otherwise, if a year is listed then results hold true only for that paper.

[7] Specifically, this measure is the infant's actual birth weight divided by the expected birth weight conditional on gestation (in weeks). This as well as other measures found in the literature are described in **Table 1.**

results are not too surprising. Age is found to increase birth weight in the 1982 paper, but non-linearly (in the form of an inverted-U) increase birth weight in the 1983 paper. The latter result here is more consistent with expectations. Young women and older women[8] have lower birth weight infants while an average age woman (which is 24 years old in this paper) is expected to have the heaviest infant. Age also increases gestation but has no effect on standardized birth weight. Finally, fertility (or the number of previous births) is found to decrease birth weight in the 1982 paper and in the translog specification of the 1983 paper, but increase birth weight in the 1983 paper (Leontief specification). In addition, greater fertility decreases the length of gestation and as a result, decreases the standardized birth weight.

A few last results were reported when some of the key variables were interacted with one another. When age and smoking were interacted in the translog model, this was found to decrease birth weight (1983). The authors explain this result by suggesting that older mothers have more likely smoked for a greater number of years than younger mothers have. Their poorer health endowment exacerbates the effect of smoking. Also, the translog results indicate that older women that have more births tend to have higher birth weight infants than young mothers who have given birth several times (1983). In this case, older women have greater success. In addition, the delay in seeking prenatal care is more critical for younger mothers and high-fertility mothers (1982).

Rosenzweig and Schultz remark that despite their efforts to accurately model the production of infant health by endogenizing a woman's behavioral inputs, their model still

[8] The age distribution is shaped like a parabola where young and older women have lower birth weight infants and an average age women (appearing at the top of the parabola) have higher birth weight infants.

suffers from omitted variable bias. This is the bias that exists due to the unknown heterogeneity among health endowments.

Empirical extensions of the basic health production function

Grossman and Joyce (1990)[9] build upon the model in Rosenzweig and Schultz (1982, 1983) in an interesting and informative way. They develop an advanced econometric technique that guides the first stage of the empirical model in this dissertation. They explain that a woman's desire to become pregnant or her "wantedness" affects her decision to either continue or terminate the pregnancy. If only women that wanted to become pregnant ultimately give birth, then these women are not a representative sample of all pregnant women. Consequently, they treat estimation of an infant health production function as a problem in self-selection. Specifically, they propose the hypothesis "that the unobserved factors that affect the decision to give birth not only affect pregnancy outcomes but also condition the behavior of women who choose to give birth during pregnancy as well" (p. 985). That is, not only do parental expectations impact birth weight but their expectations about the fetus' health endowment (in addition to their desire for the pregnancy) guide their decision about whether to continue the pregnancy. For example, they hypothesize that women who have healthily endowed fetuses and who are willing to make substantial investments in their fetuses are more likely to continue the pregnancy and experience a live birth. If this hypothesis is not controlled for, estimates obtained from the health production function will be inflated. That is, if only healthy, responsible women give birth then estimates of prenatal care use and birth weight may be upwardly biased. In light of this, the authors utilize Heckman's

two-step procedure in order to create a self-selection correction statistic. Once the statistic is obtained, it is included in the infant health production function.

Since this econometric procedure is used in the first stage of the empirical model in this dissertation, I illustrate the model that they derive below, using their notation. The three equation model is comprised of probability of birth, prenatal care and birth weight equations as seen below:

$$1.\ \pi_i = \alpha_1 z_i + u_{1i},\ u_{1i} = \alpha_2 c_i + \alpha_3 a_i + \alpha_4 e_i$$

where π represents the probability of birth, z represents the optimal number and spacing of children, u is the disturbance term, c is the cost (both monetary and psychic) of contraception, a is the cost (both monetary and psychic) of abortion, and e is the health endowment of the fetus. The birth weight equation is defined as:

$$2.\ b_i = \beta_1 x_i + \beta_2 m_i + u_{2i},\ u_{2i} = \beta_3 q_i + \beta_4 e_i$$

where b represents birth weight, x is the sex of the infant and the number of prior fetal deaths experienced by the mother, m is prenatal care, and q reflects healthy behaviors such as diet and exercise. The prenatal care equations is defined as:

$$3.\ m_i = \gamma_1 y_i + u_{3i},\ u_{3i} = \gamma_2 c_i + \gamma_3 a_i + \gamma_4 e_i$$

where y indicates the price of prenatal care including the presence of health insurance and also represents physician accessibility.

When $\pi_i \geq 0$ or $u_{1i} \geq -\alpha_1 z_i$ the expected values of birth weight and prenatal care are the following:

$$7.\ E(b_i \mid x_i, m_i, \pi_i \geq 0) = \beta_1 x_i + \beta_2 m_i + E(u_{2i} \mid u_{1i} \geq -\alpha_1 z_i)$$

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[9] A paper by Joyce and Grossman (1990) utilizes a similar procedure and estimates a similar model.

$$8.\ E(m_i \mid y_i, \pi_i \geq 0) = \gamma_1 y_i + E(u_{3i} \mid u_{1i} \geq -\alpha_1 z_i)$$

Grossman and Joyce explicitly state "[a]s emphasized by Heckman, if u_{1i} and u_{2i} are correlated, the conditional mean of u_{2i} in equation **2** is not zero, and the regressors in the equations are correlated with the disturbance term" (p. 991). They state that the same holds true for equation **3**. Therefore, the ordinary least-squares (OLS) estimates without any correction are biased.

The empirical solution is to employ Heckman's two-step procedure. The probability of birth equation is estimated as a probit. From this, an inverse Mills ratio can be computed using the following equation:

$$9.\ \lambda_i = \frac{f(\frac{\alpha_1 z_i}{\sigma_1})}{F(\frac{\alpha_1 z_i}{\sigma_1})}$$

where f is the density function and F is the distribution function of a standard normal variable. The inverse Mills ratio, λ, is included as a regressor in the prenatal care and birth weight equations and reflects unobserved heterogeneity in health endowment and the costs of contraception and abortion.

Grossman and Joyce estimate a two-stage least-squares model where the delay in seeking prenatal care is estimated in the first stage and a structural birth weight equation is estimated in the second stage. The authors utilize an instrumental variables (IV) approach in order to obtain a predicted value of prenatal care (an endogenous input) that enters into the birth weight equation, in addition to the inverse Mills ratio. Excluding measures of income and the availability of care from the birth weight equation but including them in the prenatal care equation, identify birth weight. The authors

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Therefore, only Grossman and Joyce (1990) is discussed.

acknowledge that other variables within the model could be considered endogenous. Specifically, they recognize that Rosenzweig and Schultz (1982) consider the mother's age, smoking, and parity as endogenous variables. The authors state that since separate estimation of these other variables is not necessary to explain reproductive outcomes, they alternatively treat these variables as exogenous but consider prenatal care endogenous. Additional exogenous regressors include education, age, and alcohol use, among others. In addition, a Medicaid participation dummy variable is included as a regressor in the prenatal care equation.

Results indicate that selectivity bias is found for blacks but not for whites. The authors attribute this to the fact that the cost of contraception may be higher for blacks. In addition, the potential (meaning if she had given birth rather than aborted) mean birth weight for women who aborted is 140 grams less than the observed mean birth weight. This illustrates a selectivity effect. For blacks, the greater the delay in seeking prenatal care, the lighter the infant. Although prenatal care is endogenous in the model, a Wu test indicates that prenatal care may not be endogenous. Finally, Medicaid had no significant effect.

Warner (1995, 1998)[10] are the first papers that fully include genetic factors or anthropometric[11] variables such as mother's height, prepregnancy weight, pregnancy weight gain (adjusted for gestation) and the mother's own birth weight. These variables are included to capture some of the unknown health endowment and genetic traits that are otherwise immeasurable. In addition, he develops unique measures of prenatal care: the

[10] Both papers use the same model.

[11] the study of human body measurements especially on a comparative basis. "Anthropometric," Merriam-Webster's Medical Desk Dictionary, 1997.

number of days between conception and the first prenatal visit (***DELAY***), the standardized number of prenatal visits (***VISITS***), and an interaction term of these two measures (***INTERACTION***). While the ***DELAY*** variable is a common way to measure prenatal care, the ***VISITS*** variable takes a more innovative approach by controlling for gestational age. ***VISITS*** is computed by multiplying 15 (a conservative estimate of the American College of Obstetrics and Gynecology (ACOG) recommended number of prenatal visits for a full-term (40 week) pregnancy) times the ratio of the actual number of prenatal visits made by the woman to the ACOG recommended number of prenatal visits adjusted for gestation. This measure presumes that a shorter gestation requires fewer visits. ***INTERACTION*** combines the first two measures by dividing ***VISITS*** by ***DELAY***. This variable is included in the model to account for the substitutability or complementarity between the onset of prenatal care and the number of prenatal visits. That is, Warner includes this variable in order to assess whether for example, subsequent frequent visits can compensate for extended delay in prenatal care or whether early initiation of care requires frequent follow-up visits (Warner 1998, p. 44). Warner interprets a positive coefficient on ***INTERACTION*** to suggest complementarity such that early prenatal care is more beneficial when more visits are sought. He argues that a negative coefficient indicates substitution such that early prenatal care is more beneficial when fewer prenatal visits are sought.

Both the 1995 and 1998 papers estimate similar two-stage least-squares models of birth weight and prenatal care. All three measures of prenatal care are jointly estimated in the 1st stage. Variables included in the prenatal care equation that identify birth weight are measures of income and care availability including how care is financed. Self-

payment and Medicaid are included exogenously. Included in the birth weight equation are parity, whether the pregnancy was wanted, education, smoking, age, and anthropometric characteristics. While the 1995 paper only utilizes data on non-Hispanic black women, separate regressions for black and white women are estimated in the 1998 paper. The data set used in the 1995 paper contains certificates on all births from 1980 to 1990, taken from the New York City Vital Statistics Bureau. Results from the 1995 paper indicate that black women who participate in Medicaid begin prenatal care earlier and make fewer visits compared to those that pay for prenatal care out-of-pocket. Warner's explanation for this result is that many Medicaid participants seek care at public health clinics that cannot afford to offer the recommended number of visits due to high volume. In addition, while black women that seek care earlier deliver higher birth weight infants, more prenatal visits do not yield any significant result. Although not significant, there is evidence that the onset of care and the number of visits are substitutes for one another.

The model estimated in his 1998 paper uses data from the National Maternal and Infant Health Survey (NMIHS), 1988. Results indicate that the degree of pregnancy wantedness does not significantly affect birth weight. This means that despite the woman's feelings for whether or not she wanted to be pregnant, it did not affect infant health. On the other hand, smoking both before and during the pregnancy, the mother's age, and a first birth all have a significant and negative effect on birth weight. All of the anthropometric characteristics are significant and positive in the birth weight equation. While prenatal care delay has no significant effect on fetal growth, prenatal visits do.

But, there is little evidence to support either substitutability or complementarity between delay and visits.

Other results indicate that black women experience decreasing marginal returns to visits and increasing marginal returns to delaying the onset of prenatal care. But, white women experience the opposite. In summary, the only real significant results he finds is that while delaying prenatal care has little effect on birth weight, women with lower health endowments compensate by seeking more prenatal visits and this does affect birth weight. He indicates that this result is consistent with the results found in Rosenzweig and Schultz (1982).

Although Warner's use of all three prenatal care measures is somewhat unique, he finds that severe multicollinearity exists among these variables. Therefore, to some extent, many of the results are distorted. He acknowledges that the strongest findings in the paper are with respect to the woman's physical characteristics. This implies that long-term intervention of nutrition and diet may have a more significant impact on infant health than anything else.

Rosenzweig and Wolpin (1991) utilize a different econometric approach than many of these other papers to get at the variation in infant health. Specifically, they utilize a fixed effects (within-mother) estimation technique that evaluates differences between siblings. This estimation technique allows all of the characteristics inherent to the mother to remain fixed. They estimate birth weight and gestation equations where the delay in seeking prenatal care, smoking, age, weight gain, the child's sex, parity, race, and birth order are included as exogenous regressors. Insurance status is not included.

Results indicate that health endowment, rather than observed maternal behaviors, explains 90% of the variation in infant health or birth weight, net error measurement. The authors stress these results. These results are in contrast with Rosenzweig and Schultz' premise that observed maternal behavior are significant contributors to explaining the variation in infant health.

Joyce (1994) further expands upon the literature by estimating an endogenous switching regression model that sorts women based on their level of prenatal care, as measured by a modified Kessner Index (see **Table 3**). In the first stage, a reduced-form ordered probit estimates whether women received inadequate (0), intermediate (1), or adequate (2) prenatal care. The first stage is estimated in order to construct correction statistics to include as regressors in the birth weight equations. Medicaid and insurance participation are among the regressors. In the second or primary stage, separate birth weight equations are estimated for women who received inadequate, intermediate, and adequate prenatal care as well as for whites, blacks, and Hispanics, yielding nine equations in all. Among the regressors are education, age, the infant's sex, birth order, parity, and a correction statistic.

Results indicate that many of the coefficients across the three specifications of prenatal care differed. Regardless of race, greater gains in birth weight were realized for women who went from inadequate to intermediate care versus those who moved from intermediate to adequate care. This suggests diminishing returns to more care or a non-linear effect. In addition, a statistically significant coefficient on the correction factor for an intermediate level of care (all races) suggest that the effect of prenatal care is underestimated when these are not included. All of these results suggest that unobserved

heterogeneity exist among women who demand different levels of prenatal care. Those that expect pregnancy complications utilize more prenatal care. Finally, when additional variables such as age, marital status, smoking, and first birth are endogenized within the framework, the model yields inconsistent and strange results. Joyce attributes these poor results to a lack of effective instruments.

Endogenizing the insurance choice and the impact of Medicaid[12]

Several of the papers discussed above (Warner, 1995; Joyce, 1994; Grossman & Joyce, 1990) recognize that insurance participation may affect prenatal care demand. While these studies include insurance and/or Medicaid participation as an exogenous dummy variable, they neglect to recognize that insurance participation is a choice. The theoretical framework in Moffitt[13] (1983) and Cutler and Gruber (1996) model program participation as a choice where a woman chooses the type of coverage that maximizes her utility. Empirical models in Cutler and Gruber (1996), Currie and Gruber (1996a, 1996b), and Joyce (1997) also include insurance and Medicaid as endogenous variables. Empirical evidence such as the Medicaid take-up rate, the percentage of women who are Medicaid eligible and participate, illustrates that Medicaid participation is a choice. In addition, many states have invested in Medicaid outreach programs in order to inform and attract women who are Medicaid eligible to participate. Several studies (see **Table 4**) have shown that the take-up rate for public assistance programs including Medicaid is far less than 100% or on average around 50%. Furthermore, other studies have shown that one-third (Cutler & Gruber, 1996) to one-half (Dubay & Kenney, 1997a) of privately

[12] Janet Currie, Jon Gruber, and David Cutler conduct a number of studies pertaining to this topic that are summarized in Gruber, J. (1996). Health insurance for poor women and children in the U.S.: Lessons from the past decade. NBER Working Paper Series, 5831, 1-53.

insured women drop their private insurance in lieu of Medicaid upon becoming eligible. This phenomenon, called crowding-out, further illustrates that insurance coverage is a "choice". The papers that follow treat Medicaid and/or private insurance participation endogenously in their theoretical and empirical models.

Moffitt (1983) incorporates a welfare stigma into a utility maximization framework that reconciles the lack of participation by eligible individuals. This measure of stigma represents the disutility that an individual faces by participating in a welfare program. There are four commonly documented reasons why welfare participation suggests disutility. The first is this notion of welfare stigma[14]. Welfare recipients have been known to suffer from feelings of low self-esteem while participating in welfare. This is particularly true if welfare is viewed as a long-term "handout".[15] The second reason is the high transactions costs of applying and enrolling in welfare programs. These programs often require lengthy application and approval processes that diminish the value of the benefit. Third, eligible individuals may not be aware of their eligibility. This is particularly relevant anytime the eligibility requirements are expanded in a program. **Table 5** reflects state outreach efforts intended to increase awareness about eligibility. Finally, but only relevant to Medicaid, is that the provider network associated with the Medicaid program is often inadequate to serve the Medicaid population. This means that despite having insurance, Medicaid participants are often turned away by a

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[13] Note that Moffitt actually models welfare participation not insurance or Medicaid participation.
[14] Bassi, L.J. (1990). Employment and welfare participation among women. Economic Inquiry, 33, 222-238 also provides a model of welfare stigma.
[15] Today's TANF programs are designed to reduce the stigma that has been long associated with welfare. Today's programs provide assistance to families on a more temporary basis - to get families out of a rut - rather than provide a lifetime handout. Obviously, one of the primary goals of TANF is to reduce welfare caseloads.

growing population of non-participating physicians. This issue is changing and is discussed later. Moffitt incorporates stigma into the model in two different ways. The first way does not take into account the amount of benefit received by the participant. This means that some fixed amount of stigma exists regardless of how much benefit is received. The utility function is written as:

$$U(Y + PB) - \phi P,\ \phi > 0$$

where Y is income, B is the welfare benefit, P indicates whether the individual participates, and ϕ reflects the stigma associated with participation. An individual will participate in a welfare program only if the utility from the welfare benefit outweighs the disutility from participation:

$$U(Y + B) - \phi > U(Y) \text{ or } U(Y + B) - U(Y) > \phi .$$

Therefore, Moffitt suggests that anything that increases the size of the benefit will increase the likeliness of participation. The second formulation of the model takes into account a variable component of stigma, γ, that varies with the amount of the benefit:

$$U(Y + \gamma PB) - \phi P,\ \phi > 0,\ 0 < \gamma < 1 .$$

In essence, this says that the utility derived from a dollar of welfare benefit is less than the utility derived from a dollar of non-welfare income.

When put to the empirical test, results indicate that a generic welfare stigma does exist and that a dollar of welfare income is as good as a dollar of non-welfare income, but that an individual derives even more utility from the former[16]. Moffitt offers two possible explanations for this surprising result. The first is that AFDC income may also imply receipt of Medicaid and Food Stamps benefits. These are not explicitly controlled for in

the model. The second explanation is that the non-welfare wage imperfectly measures the return to work since there are fixed costs associated with returning to work. In a sense, the value of a dollar of welfare income is overestimated while the value of a dollar of wages is underestimated. This paper not only informs the model in this dissertation but also offers some insight into the interpretation of results.

Cutler and Gruber (1996) provide an excellent discussion of the factors that enter into a woman's decision making process when she decides to either purchase private insurance or participate in Medicaid. The following paragraphs are taken directly from their paper.

> Consider a woman of childbearing age or a child, deciding on their insurance choice...[M]ore generous plans offer a greater range of providers or cover a wider set of medical services. People choose between more generous insurance and other goods [shown in **Figure 1**]. People valuing insurance highly (i.e. those demanding the highest quality providers) will choose a policy such as ***D***, while those valuing insurance less highly will choose a point such as ***E***.
>
> Now the government introduces free public insurance with generosity ***M***. On paper, Medicaid is a very valuable policy: almost everything is covered, and there is little or no cost sharing. For many reasons, however, the value of Medicaid is below that of private policies. Because of low Medicaid reimbursement rates, providers are often reluctant to treat Medicaid patients (Currie, Gruber, and Fischer, 1995), thus reducing the value of coverage. In addition, individuals may not want to be enrolled in public programs, because of the stigma associated with public programs or the difficulty in enrolling. Finally, the value of Medicaid may be low because individuals may have difficulty shifting from Medicaid back into private coverage if they have preexisting medical conditions. We thus show the value of the Medicaid package as below the value of most private policies.
>
> Individuals cannot purchase a supplement to Medicaid...[therefore] must consume insurance exactly in the amount of ***M***. If they want any higher quality insurance, they return to the original budget constraint. The budget

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[16] This suggests that $\gamma > 1$.

> constraint with Medicaid is therefore ***ABMC*** [see **Figure 1**]. In response to this public coverage, people with low values of private insurance (such as ***E***) will choose to enroll in the public sector, while individuals with a high valuation of insurance (such as ***D***) will choose to retain their private insurance. (Cutler and Gruber, 1996, pps. 393-394.)

Cutler and Gruber estimate an empirical model of crowd out. Specifically, they estimate three separate probits for Medicaid, private insurance, and no insurance:

$$COV_i = \beta_1 ELIG + X_i\beta + \sum \alpha_s state_i + \sum \alpha_t time_i + \varepsilon_i$$

where ***ELIG*** is a measure of the Medicaid eligibility status for the individual. They find that it is problematic to impute the actual Medicaid eligibility for each individual since the rules are too complex. Therefore, they use an exogenous measure of state Medicaid generosity that takes into account household size and weights it according to national population data. A similar approach is used in this dissertation, except that it is not weighted. They estimate Medicaid, private insurance, and no insurance as three univariate probits rather than as a bivariate probit. This modeling specification also guides the empirical model of this dissertation. The primary inclusion of Cutler and Gruber's (1996) paper here is to guide the modeling of my empirical section. Using aggregate data, their model evaluates the extent to which individuals drop their private insurance in lieu of Medicaid. While their model allows for the direct effect of eligibility on health outcomes to be captured, their model does not reveal the effect that Medicaid has on outcomes. The results obtained are not as relevant to this dissertation, except for their estimate of crowding out. This is discussed later in the policy simulation chapter.

Currie and Gruber (1996b) use aggregate data to estimate low birth weight and infant mortality production functions. Low birth weight is measured as the number of

infants born under 2500 grams per 1000 births, while infant mortality is measured by the number of deaths per 1000 births. Along similar lines to Cutler and Gruber (1996), the authors evaluate the impact of Medicaid eligibility rather than Medicaid participation on infant health. They construct simulated eligibility in three different ways. The first method simulates eligibility for all women in the sample in 1979, in the same way as Cutler and Gruber (1996). The second way links eligibility to cash assistance (such as participation in the AFDC program) which typically has more strict eligibility requirements than Medicaid alone. The third way includes women who meet only the medical assistance (Medicaid) eligibility criteria.

The authors estimate these models twice, once as reduced-form models where eligibility is entered directly into the model, and a second time using an instrumental variables (IV) approach (where eligibility is instrumented). Results indicate that an increase in eligibility reduces the incidence of low birth weight. The effect that is reported to be the strongest uses the second measure of eligibility. The authors attribute this result to a few things. The first is that the Medicaid take-up rate is much higher among women who become eligible for cash assistance, thus greater gains are earned from participation. Secondly, these women are more needy (in general) than women in the other two groups and are more aware of public assistance programs.

Joyce (1997) extends the analysis of Medicaid participation one step further and analyzes the effect of New York's Prenatal Care Assistance Program (PCAP), a program offering enriched prenatal services to Medicaid women, on birth weight. All of the women in the sample are Medicaid participants, but only some of them are enrolled in the PCAP program. The author's objective is to determine whether PCAP participants

receive more prenatal care than non-PCAP participants do and whether PCAP participation increases birth weight. He uses four different measures of birth weight including the actual birth weight and three dichotomous measures of low birth weight (less than 2500 grams), very low birth weight (less than 1500 grams), and term low birth weight (less than 2500 grams and greater than 37 weeks gestation). These measures are summarized in **Table 2**.

Joyce estimates several models, stratifying by the type of eligibility (whether the woman is eligible for cash assistance or only medical assistance). Age, race, education, marital status, parity, and the infant's sex are among the exogenous regressors in the health production functions. He estimates the model once, including PCAP exogenously, and a second time using an IV approach where a set of health districts by year and the number of PCAP provider sites by health area are the instruments.

Results from the OLS model indicate that PCAP women have infants weighing 50 grams more and have a lower incidence of low birth weight than non-participants. When preterm infants are excluded, the results are smaller but remain statistically significant. However, results from the 2SLS model indicate that PCAP participation has no effect on birth weight or the incidence of low birth weight. Furthermore, a Wu-Hausman test reveals that OLS and 2SLS estimates differ and that the OLS estimates are biased.

The next set of articles differs from the previous ones by evaluating the effect of Medicaid participation and the Medicaid expansions on children's use (rather than pregnant women's use) of medical care and on child health outcomes. While the *results* obtained are not very useful in providing guidance to the model in this dissertation, these

papers are useful in the sense that they provide some insight on *how* to empirically model the relationship between Medicaid use, health care utilization, and outcomes.

Currie and Thomas (1995) evaluate the impact of having Medicaid and private insurance on the utilization of routine health checkups. They estimate a series of reduced-form equations on whether the child had a routine health checkup in the past month, three months, six months, one year, and two years. Exogenous variables include income, parent's education, and urban, in addition to Medicaid and private insurance dummy variables, where the excluded category is no insurance. All explanatory variables were interacted with race in order to distinguish the effects between white and black children. The authors believe that white and black children differ substantially by the type and generosity of their household resources, to the extent that white children are far more likely to have private insurance and black children are more likely to participate in Medicaid. Results confirm differences by race.

In a similar paper, Currie and Gruber (1996a) evaluate the effect of Medicaid eligibility on child health care utilization and child mortality. In this paper, Medicaid eligibility (not participation) is treated both exogenously and endogenously. That is, the models (with different measures of utilization and mortality) are estimated once as reduced-from equations and then again using a simulated instrumental variables approach.

In their reduced-form model, imputed Medicaid eligibility[17] (based on household income) for each child is included as a regressor along with other variables such as race, parent's education, income, and rural. While the direct effect of eligibility on utilization

can be captured in this model, the authors point out that this model suffers from bias in several ways. The first way is that a sick child may cause a parent to work less, reducing income, and thus affecting eligibility. This is an endogeneity bias since eligibility is determined within the model. The second way is that this imputed measure suffers from measurement error. The authors suggest using a simulated instrument of eligibility as an alternative to imputing eligibility in order to eliminate the endogeneity and measurement biases. The instrument is constructed by selecting a national random sample of children, ages zero to fourteen, in each year, and calculating the fraction that would be eligible for Medicaid given the rules in each state in that year. This measure is correlated with the state's legislative environment, but not with individual specific economic or demographic characteristics (p. 446). The reduced-form empirical model in this dissertation follows from this model.

Recent trends in Medicaid

In some way all of the articles that appear above inform either the theoretical or empirical model (or both) in this dissertation. Several of the articles illustrate how Medicaid participation and eligibility are modeled into the health production function framework. While these articles provide some guidance as to how Medicaid may affect medical care demand and health outcomes, a few important aspects are overlooked. Only Currie and Gruber (1996a) show how changes in the Medicaid program over time affect the key variables of interest, although their analysis using several data sources with aggregate data. This dissertation uses one source of individual data making my model more cohesive. The policy simulation that I conduct in **Chapter IV** illustrates the effect

[17] This is a similar measure to the one used in Cutler and Gruber (1996).

of a change in Medicaid eligibility on prenatal care and birth weight. However, many other aspects of the Medicaid program have changed considerably over the past decade. One of the most important changes is the move to Medicaid managed care. A number of articles (including Felt-Lisk & St. Peter, 1997; Rosenbaum, 1997; Welch & Wade, 1995) that are discussed in **Chapter IV** illustrate the ways in which Medicaid managed care has changed the health care environment.

Epidemiological insight in defining inputs

Prenatal care

In many of the studies discussed above as well as in my empirical model, prenatal care plays a dominant role in both the theoretical and empirical models. This is not without reason. Many studies in the epidemiological and health literature have shown that adequate prenatal care is an essential input into the production of a healthy infant. This substantiates that there is some correlation between prenatal care and infant health or birth weight. In 1989, the U.S. Public Health Service Expert Panel on the Content of Prenatal Care reported that women who begin seeking prenatal care during their first trimester have better pregnancy outcomes than those with less or no prenatal care (Witwer, 1990). However, despite this research, some studies have found that women with no prenatal care bear healthy infants (Higgins & Burton 1996). When incorporating prenatal care into a model, there are several things that one must take into account. The first is to determine the appropriate measurement of prenatal care whether it is the onset of prenatal care, the number of visits, or some combination of both that also accounts for gestation. **Table 3** illustrates a variety of prenatal care measures used in the economics

and epidemiological literature. A more detailed discussion of these measures as well as a discussion of prenatal care indices (Alexander and Kotelchuck, 1996) appears in the **Descriptive statistics discussion** section. In addition, when prenatal care is included as an endogenous variable in the model, appropriate instruments that explain the variation in prenatal care must be found. This is where the epidemiological and health literature can provide some insight.

Two of the most important elements to consider when "measuring" prenatal care are the onset of prenatal care and the frequency of visits. Traditionally, an accepted standard set by the American College of Obstetricians and Gynecologists (ACOG) recommends that pregnant women seek approximately 13 prenatal visits during the course of a full-term pregnancy. These visits should begin during the first six weeks of pregnancy, occur monthly for the first six months, bimonthly during months seven and eight, then weekly until delivery. However, a survey article written by Witwer (1990) discusses an alternative schedule recommended in the 1989 report by the U.S. Public Health Service Expert Panel on the Content of Prenatal Care. This report strays from the ACOG recommendations and suggests that proportionately more visits should occur at the beginning of pregnancy but less overall visits (nine for nulliparous women and seven for parous[18] women) are sufficient if a woman is not considered at high risk for pregnancy and/or birth complications. More specifically, the report suggests that a continuous risk assessment should occur throughout pregnancy such that the ultimate number of visits is determined based on this assessment.

[18] Nulliparious indicates that a woman had not previously had a pregnancy while parous suggests that she has had a previous pregnancy.

While there remains some debate regarding the sufficient number of prenatal visits, it is generally accepted that prenatal care should begin as early as possible. The Public Health Service even suggests that a preconception visit, within a year of conception, is ideal. This type of visit can identify any medical conditions, personal behaviors and environmental hazards that are typically associated with poor pregnancy outcomes. Once identified, these conditions can be altered and corrected prior to conception. Essentially, these are the same reasons used to justify the necessity of the early onset of prenatal care.

Witwer (1990) discusses a wealth of data published in a 1989 Alan Guttmacher Institute (AGI) in-depth report regarding prenatal care utilization and birth outcomes in the U.S. from 1984-1986. The first section of the report focuses on prenatal care use by different sub-groups of women and across different regions of the U.S. Overall, the report finds that two-thirds of American women receive adequate prenatal care, defined as beginning in the first four months of pregnancy and consisting of at least 80% (10.4 visits) of the ACOG recommended number of visits (13 visits). 18% of women receive intermediate prenatal care, also defined as beginning during the first four months of pregnancy but including between 50% and 79% (6.5-10.3 visits) of the recommended number of total visits. Finally, the report finds that the remainder (16%) receives inadequate care. These women began prenatal care after the first four months of pregnancy or received less than half (6.5 visits) of the recommended number of prenatal care visits.

To shed some light on the specific sub-groups of women receiving inadequate prenatal care, the authors find that of women with less than a high school education,

unmarried or teenage that 30%-33% received inadequate prenatal care. Across ethnic lines, 13% of whites, 27% of blacks, 30% of Hispanics and 32% of Native Americans receive inadequate care. Finally, women in the South are the most likely to receive inadequate prenatal care. Broken down by sub-group, black women in the Northeast and teenagers, older women, unmarried women and Hispanic women in the South are at highest risk.

Finally, the authors discuss statistics on those that received delayed (beginning in the second trimester) and late (beginning in the third trimester) prenatal care. This accounts for 24% of all American women, 21% of whites, 39% of blacks, 39% of Hispanics and 42% of native Americans. Other studies such as Pettiti, Coleman, Binsacca, and Allen (1990) find that white women are more likely to begin prenatal care in the first trimester than black women are.

Barriers to prenatal care

The economic studies surveyed earlier stress the importance of identifying good instruments when endogenizing prenatal care. While many of these studies attributed differences in prenatal care utilization to unobserved heterogeneity in health endowments. where women with poorer endowments seek more care, epidemiological studies have identified several barriers that may prevent women from seeking adequate prenatal care.

Piper, Mitchel & Ray (1996b) focus their study on the relationship between the density of obstetric providers and the onset of prenatal care. They find that there is no significant relationship, specifically that the availability of obstetric care does not affect the onset of prenatal care. However, they did find that the following factors contributed

to a delay in the onset of prenatal care: age less than 16, lack of high school education, three or more previous pregnancies or being unmarried.

Taggart and Mattson (1996) use a sample of 502 pregnant women from California Women, Infants, and Children (WIC) and other public health clinics to determine the incidence of battering and whether battering is correlated with a delay in seeking prenatal care. The authors find that while the onset of prenatal care did not differ across ethnic groups of African American, Caucasian American and Hispanic women, prenatal care was delayed an average of 6.5 weeks due to battering. On average, battered African American women began prenatal care at 29.7 weeks, Hispanic women at 33 weeks and Caucasians at 31.7 weeks. While an average of 13.7% of these women reported that the onset of prenatal care was delayed due to battering, 20% were physically abused during pregnancy and 43.8% had faced some type of physical abuse during their lifetime. Not only were physical signs of battering, such as bruises among the reasons described as attributing to the delay in seeking prenatal care but as important were social circumstances such as fear of the controlling abuser and isolationism. In addition, women also reported "involuntary/forced sex" as a reason that caused the delay.

Maternal depression and infant health

Many of the studies discussed in the first section are extensions of the health production function developed by Rosenzweig and Schultz (1982). Their model stresses the importance of including parental behavioral inputs in the production process. Since the development of their model, the literature has recognized several factors including prenatal care, anthropometric measures, fertility decisions, and smoking as significant inputs in the production function. However, to date, the economics literature has

neglected to acknowledge maternal depression as an important input that not only may affect infant health but may also affect the choice and productivity of the other inputs.

The epidemiological literature has evaluated the relationship between maternal depression and infant health. In fact, several recent studies (Field, 1998; Jones, Field, Fox, Lundy, & Davalos, 1997; Dawson, Frey, Panagiotides, Osterling, & Hessl, 1997a; Dawson, Panagiotides, Klinger, & Spieker, 1997b; Locke, Baumgart, Locke, Goodstein, Thies, & Greenspan, 1997) have shown that infants of depressed mothers show signs of poorer health as measured by dysregulation[19] and reduced left frontal (responsible for positive emotions) or increased right frontal (responsible for negative emotions) activation in the brain.

Specifically, Field (1998) characterizes dysregulation in infants in the neonatal period by " limited responsivity on the Brazelton test, excessive indeterminate sleep [shown to be negatively associated with IQ scores at age 12], and elevated norepinephrine and cortisol levels" (p. 200). That is, newborns of depressed mothers showed inferior scores on recognizing inanimate objects and on depression and robustness factors. They also demonstrated more stressed behaviors and had elevated levels of stress hormones than newborns of non-depressed mothers.

Many studies including Dawson et al. (1997b) have used electrical activity in the brain as a measure of depression in women and infants. In order to discuss this, here is a quick epidemiological lesson on brain activity. The left frontal region of the brain is responsible for the expression of emotions associated with the external environment such

[19] Impairment of regulatory mechanisms such as those governing concentration of a substance in the blood or the function of an organ. "Dysregulation," Merriam-Webster's Medical Desk Dictionary, 1997.

as happiness, interest, and anger. The right frontal region reveals the expression of mostly negative emotions associated with withdrawal including disgust and sadness (p. 650). It has been found that depressed individuals exhibit reduced left frontal region activity, even during periods of remission from showing depressive symptoms. Dawson and his co-authors measured the electrical brain activity in the left and right frontal regions in a group of infants of both depressed and non-depressed mothers. The Center for Epidemiological Studies Depression Scale (CES-D)[20] was used to assess whether or not a mother was depressed. A score of 16 or greater (out of a possible 60) indicates depression. Results indicate that increased right frontal brain activation, the region responsible for mostly negative emotions, was found in infants of depressed mothers. The authors explain that this may reflect these infants' greater propensity to reveal negative emotions or that negative emotions are expressed more intensely than in infants of non-depressed mothers. In a similar study, Dawson et al. (1997a) found that infants of depressed mothers do exhibit reduced left frontal brain activity.

Finally, Locke et al. (1997) conducted a study of preterm births (less than 34 weeks gestation) of depressed and non-depressed mothers, as assessed by CES-D. Neonatal infant health status measures include bronchopulmonary dysplacia (BPD) and intraventricular hemorrhage (IVH), among others. While birth weight and gestation did not differ between infants of depressed and non-depressed mothers, infants of depressed mothers had significantly worse outcomes in the measures described above.

While the epidemiological literature has shown a significant link between maternal depression and infant health, there is always room for more research to be

[20] This measure is discussed in greater detail in the empirical section as it is the same measure used in this

conducted. For instance, there have been no studies to date that evaluate the specific relationship between maternal depression and birth weight. The health production function framework would be an appropriate model to evaluate such a relationship. In addition, an empirical analysis using modern econometric techniques could accurately determine whether any "true" relationship exists between the two while controlling for any confounding factors.

Depression and individual functioning

Several studies in recent years have shown that people with depressive symptoms and depressive disorders often suffer from significant impairment of social and interpersonal functioning including the capacity to work, relate to friends and family and even enjoy leisure time. In light of this research, it is reasonable to infer that depression may affect a woman's choice of prenatal care as well as other behaviors during pregnancy. In fact, in a study of women who had minimal prenatal care, Joyce, Diffenbacher, Greene, and Sorokin find depression and denial were higher in that group; albeit, this is not a causal study. To date, there is little research that investigates the link between depression, the demand for prenatal care and other healthy behaviors.

Table 6 illustrates two of these studies that reveal the extent to which depressed individuals function both physically and emotionally poorer than groups of individuals who suffer from either no illness or a chronic illness. Specifically, Wells et al. (1989) find that in six different categories of physical and emotional functioning that individuals with no chronic condition function better than those with either a depressive disorder or depressive symptoms. In a similar study, Hays et al. (1995) find that only individuals

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dissertation.

afflicted with congestive heart failure function poorer than those with a depressive condition. Furthermore, other studies such as Broadhead et al. (1990) indicate that individuals with major depression are 4.78 times more likely to miss work than individuals who show no sign of depressive symptoms. These studies impart significant implications since depression afflicts anywhere from 10% to 39% of the general population (see **Table 7**). Women in particular suffer from even higher rates of depression (on average) as well as suffer from greater impairment than men.

Conclusion

This dissertation seeks to join the health and epidemiological literature with the economics literature while at the same time closing a few important gaps. First, the health production function literature in general does not recognize the endogeneity of Medicaid nor the quality effect that is has on birth weight. Both the empirical and theoretical models in this dissertation include Medicaid and private insurance as choice variables. Specifically, the welfare stigma discussed in Moffitt (1983) is entered into the theoretical model in order to influence one's choice of health insurance. In a related strain, a private insurance "safety net" quality effect, assumed to be positive, is also included. Additionally, Medicaid and private insurance are included in the infant health production function as it is expected to have a quality effect on birth weight. Second, the health literature provides some evidence on the effects of depression and on the behavior of depressed individuals. Using the information learned here depression is incorporated into my theoretical and empirical models. While the economics and health literature

provide a solid foundation for the models developed in this dissertation, my dissertation takes the literature a few steps further by addressing a few of its shortcomings.

CHAPTER III

MODEL OF MEDICAID, DEPRESSION, PRENATAL CARE AND BIRTH WEIGHT

Introduction

This chapter presents the theoretical and empirical models of Medicaid, depression, prenatal care, and birth weight. The models developed here draw upon several papers in the economics literature. The health production function framework proposed by Rosenzweig and Schultz (1982) guides the development of the theoretical model. One extension of this model is the incorporation of a welfare stigma proposed by Moffitt (1983). The second extension is that Medicaid participation and private insurance coverage are treated as a choice. The empirical model utilizes the sample selection correction statistic from Joyce and Grossman (1990) and the endogeneity of Medicaid and insurance from Cutler and Gruber (1996). The empirical model is also similar to Warner (1998) particularly because it uses the same data set. However, three additional components make the models in this dissertation unique and a contribution to the literature. The first is the incorporation of depression into both the theoretical and empirical models. The complexity of this extension is discussed in more detail in the following paragraph. The second is that the endogenization of Medicaid and insurance coverage (taking into account Medicaid eligibility) is highlighted in both the theoretical

and empirical models. Finally, a treatment effects model is used to evaluate the impact of depression, Medicaid and insurance coverage on prenatal care and birth weight. This allows for the direct effect of depression, Medicaid and insurance (on the key variables) to be captured unbiasedly.

Throughout the theoretical and empirical models, maternal depression is difficult to incorporate since it is composed of two distinct components: a long-term chronic component and a transitory component. The literature indicates that depression may be caused or instigated by underlying genetic factors or a chemical imbalance in the brain (that are out of the individual's control) and by life events (that may be within our control). In economist terminology, this means that factors that induce depression are both exogenous and endogenous, respectively. One component of depression is unavoidable and the other component is brought on by the actions of the afflicted. It is assumed that the long-term component is exogenous while the transitory component, most likely brought on by a life event, is more endogenous. In the context of this dissertation, post-partum depression following childbirth is considered to be the predominant transitory component. Despite this distinction, it remains difficult to separate out these two components of depression, particularly in the empirical model. The empirical measure of depression, the Center for Epidemiological Studies Depression Scale (CES-D Scale) does not distinguish among these two components of depression. This issue is discussed in greater detail in the theoretical and empirical models as an attempt is made to appropriately incorporate both components of depression.

This chapter is structured as follows. The next section outlines the theoretical model. This is followed by general and detailed descriptions of the data used. The

remainder of the chapter illustrates the empirical model and any statistical issues that arise in its estimation. Sample selection correction statistics are discussed, followed by the development of the structural model. Included in this section is a description of the variables that appear in each equation. Since the structural-form of the empirical model is somewhat restrictive, reduced-form models are also estimated. The development of the structural and reduced-form models is followed by a discussion of the results. Finally, I conduct a poor health outcome or low birth weight study to evaluate the factors that effect this important population.

Theoretical Model of Infant Health Production, Medicaid, and Depression

The theoretical model in this dissertation extends the health production function/utility maximization framework developed in Rosenzweig and Schultz (1982) and the incorporation of a welfare stigma found in Moffitt (1983). In addition to the usual factors that affect utility, it is assumed that the woman's type of health insurance coverage also affects her overall utility, indirectly through the budget constraint and directly through welfare stigma. Since three different types of insurance coverage are considered here, no insurance/self-pay, Medicaid, and private insurance, three utility maximization problems are derived. It is important to emphasize again that insurance coverage is a choice variable. That is, I assume that a woman can choose to be privately insured, participate in Medicaid, or be uninsured. However, in the empirical model, Medicaid dollar income eligibility is considered exogenous. While I assume that women can adjust their income to become Medicaid eligible or seek a job that provides private insurance, women cannot affect state level Medicaid eligibility. For simplicity, in the

theoretical model, all women are assumed to be Medicaid eligible. The following models determine utility under each of the three types of insurance coverage. The three utility levels are then compared in order to determine the type of coverage that yields the highest level of utility. That is, a woman chooses the type of coverage that maximizes her utility.

It is important to add that risk preferences are not incorporated into the theoretical model. Risk preferences are often incorporated into an individual's insurance decision when the individual does not have clear expectations about her future health care needs. Pregnant women, the sample of interest in this dissertation, have a well-defined knowledge of at least some of their future health care needs (at least for nine months). They understand that they will need to seek prenatal care and other medical services on a regular basis during the pregnancy and at delivery. It certainly may be argued that some pregnant women (for example, women at higher risk of poorer health outcomes) may have or at least perceive themselves as having different health care needs as other pregnant women. (In an HMO study, Welch and Wade (1995) believe that Medicaid participants use medical services at a greater volume and intensity than privately insured individuals.) Nonetheless, it remains likely that these women have a better-defined knowledge of their health care needs, at least in the more immediate future, than the average population. Therefore, the theoretical model assumes no risk preferences.

Self-pay case

This first scenario assumes that a woman chooses to demand no health insurance coverage[21]. Given that there are millions of uninsured individuals in the U.S., this is a likely scenario. There are several reasons why a woman may choose to be uninsured

rather than participate in Medicaid or purchase private insurance. The welfare stigma associated with Medicaid participation may be high enough to discourage participation. Alternatively, a woman may choose not to become eligible to receive Medicaid (by maintaining too high an income) or choose not to obtain employment with private insurance as a benefit. [In addition, not all women know that they are Medicaid eligible. However, Medicaid outreach programs are hoping to alleviate this likely scenario.] Finally, the price of private insurance premiums may exceed a woman's willingness-to-pay for health insurance.

If an uninsured woman demands medical care, she pays a price of P^{NO} for each visit and obtains a level of quality that is inferior to both Medicaid and private insurance quality. Often, physicians view uninsured patients as "bad debt". Physicians face the risk of not receiving payment for their services. Unlike insurance or even Medicaid, there is no guarantee of any payment. As a consequence, uninsured patients likely receive substantially lower quality care than insured patients.

Her utility function is defined as:

$$1.\ \max_M U(H, D^{LT}, D^T, X) \quad \textit{utility function}$$

where H reflects her infant's health, depression is composed of D^{LT}, a parameter that represents her long-term mental state, and D^T, a transitory component that reflects shorter episodes of depression such as post-partum, and X is a composite commodity. Both components of depression are included in the utility function since they both affect utility.

[21] Recall that I am allowing insurance coverage, including no coverage, to be a choice.

This point is elaborated on later. This maximization process is subject to the production of infant health,

$$2.\ H = H(M, D^{LT}, Z^{H}) \quad \textit{health production function}$$

the production of transitory depression,

$$3.\ D^{T} = D^{T}(M, H, Z^{D}, D^{LT}) \quad \textit{transitory depression production function}$$

and a budget constraint,

$$4.\ P^{NO}M + X = I \Rightarrow X = I - P^{NO}M \quad \textit{budget constraint},$$

where the price of the commodity is normalized to one.

Referring to equation **2.**, prenatal care, M, is expected to enhance infant health, H, while long-term or chronic depression, D^{LT}, is expected to adversely affect infant health, as has been shown in the literature by Dawson et al. (1997b) and others. In addition, other variables such as a woman's anthropometric characteristics including a mother's own birth weight and her height (as suggested by Warner, 1995 & 1998), genetic endowment, and other maternal behaviors, Z^{H}, are expected to directly affect (either enhance or detract from) infant health.

Equation **3.** illustrates the production of the transitory (or post-partum) component of depression that is considered endogenous in the model. This means that D^{T} is an outcome of the production process. However, it is assumed that long-term depression, D^{LT} is predetermined or exogenous in nature and its presence increases the chance that a woman suffers from post-partum depression. Prenatal care, M, is included since it may lead to the detection and treatment of depression (or the assurance that one is not depressed). That is, a prenatal care provider may take action during the pregnancy to

alleviate any depressive symptoms that may occur following pregnancy. Seeking prenatal care may not only affect the health of the fetus but may also alleviate any health problems, including mental health issues, faced by the woman. An unhealthy infant, measured by H, may increase the chance that a woman will suffer from post-partum depression. That is, a "poor" life event such as bearing an unhealthy child may trigger depression. Finally, other characteristics, Z^D, such as social support, are expected to also directly affect (either enhance or retract from) the onset and severity of depression.

Equation **4.** represents the budget constraint where P^{NO} is the self-pay price per visit of prenatal care, M, I is income, and X is a composite commodity. It is assumed that the budget constraint under the self-pay/uninsurance case is quite different from that of the Medicaid and private insurance cases. These differences are highlighted later.

If prices are greater than zero and the utility function is continuous, then the utility maximization problem has a solution[22]. The quasi-concave utility function illustrated in **1.** is maximized by choosing the optimal quantity of M. Substituting the constraints **2.**, **3.**, and **4.** into the utility function yields:

$$5.\ U\left(H(M, D^{LT}, Z^H), D^{LT}, D^T(M, H(M, D^{LT}, Z^H), Z^D), I - P^{NO}M\right).$$

An interior solution requires that a consumer's marginal rate of substitution between any two goods must be equal to their price ratio. If this was not the case, then a

[22] If $p>>0$, then the budget set $B_{P,I} = \{X \in \mathbb{R}^L_+ : P * X \leq I\}$ is a compact set because it is both bounded for all $X \in B_{P,I}$ and closed. The result follows from the fact that a continuous function always has a maximum value on any compact set.

consumer could do better by marginally changing her consumption. The first order condition (FOC) is the following[23]:

$$6.\ U_M = U_H H_M + U_{D^T} D_M^T + U_{D^T} D_H^T H_M - U_X P^{NO} = 0$$

❶ ❷ ❸ ❹

The first order condition illustrates all of the benefits from getting prenatal care (M). The first two effects are of the second order meaning that prenatal care directly affects other variables (infant health and depression) that directly enhance utility. ❶ It is expected that prenatal care enhances infant health ($H_M > 0$). Since the woman derives utility from having a healthy infant ($U_H > 0$), prenatal care indirectly enhances utility ($U_H H_M > 0$). ❷ Prenatal care also reduces the likeliness of post-partum depression ($D_M^T < 0$) which is important since a woman's utility is diminished if she suffers from post-partum depression ($U_{D_T} < 0$). Therefore, prenatal care also indirectly enhances utility through its effect on depression ($U_{D_T} D_M^T > 0$). ❸ Prenatal care also has a positive third order effect on utility ($U_{D^T} D_H^T H_M > 0$) through similar channels described above. That is, prenatal care enhances infant health ($H_M > 0$), that in turn alleviates depression ($D_H^T < 0$), which in turn enhances utility ($U_{D_T} < 0$). ❹ Finally, as prenatal care increases, more dollars must be devoted toward prenatal care (and taken from the consumption of X) in order to maintain the same level of care. As a result, utility is lost from having to forgo some quantity of X.

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[23] Subscript denotes partial derivative; eg. $U_M = \frac{\partial U}{\partial M}$

The rule that assigns the set of optimal consumption vectors in the utility maximization problem to each price-income situation is known as a Walrasian or ordinary demand function. Suppose that the utility function is a continuous function representing a locally nonsatiated preference relation defined on the consumption set $X=\mathbb{R}^{L}_{+}$. Then the Walrasian demand function (given that X is single valued for all prices and income) possesses the properties of homogeneity of degree zero and Walras' law. If the preference relation is strictly convex so that the utility function is strictly quasiconcave, then the demand function consists of a single element. In this model, optimal prenatal care demand is the following and is a function of all the exogenous variables in the system:

$$7.\ M^{*}(D^{LT}, Z^{H}, Z^{D}, P^{NO}, I).$$

For each price and income vector greater than zero, the utility value of the utility maximization problem is denoted by $V(P,I)\in\mathbb{R}$. This indirect utility function is equal to $U(X^{*})$ for any $X^{*}\in X(P,I)$. In other words, $D^{T}{}^{*}(.)$, $H^{*}(.)$, and $X^{*}(.)$ are solved residually and substituted into the utility function, thus maximizing utility, $U^{*}(M^{*}(.))$. Since the optimal level of utility depends on $M^{*}(.)$, utility is an indirect function of income and all of the exogenous variables in the system. The indirect utility function can be written as:

$$8.\ V^{NO}(D^{LT}, Z^{H}, Z^{D}, P^{NO}, I)$$

where $V(.)$ is the indirect utility function. The indirect utility function illustrates how utility is related to exogenous variables in the problem. This level of indirect utility will be compared to the indirect utility functions under Medicaid and private insurance.

Medicaid case

The Medicaid program has provided a safety net to millions of Americans who would otherwise have no access to any health insurance coverage. However, research suggests that upwards of 50% of Medicaid eligible women choose not to or simply do not participate in the program. Not all women who are Medicaid eligible have the knowledge that they are eligible. As mentioned, states are employing outreach efforts to reduce this imperfect knowledge[24]. An explanation offered by Moffitt (1983) and others is that there are high transaction costs to participating in welfare programs. These include a "stigma" that reflect low self-esteem in taking a handout from the government and bureaucratic paperwork. Often, women enroll in welfare programs in order to become eligible to receive Medicaid. With the transition from Aid to Families with Dependent Children (AFDC) to Temporary Assistance to Needy Families (TANF) in 1996, stringent[25] TANF work requirements and the five-year national time limit may discourage participants from welfare, and thus, Medicaid[26]. However, the model developed here uses data that occurred before the transition to TANF. Finally, Cutler and Gruber (1996) add that Medicaid recipients have less access to quality care since many providers will not serve this population, making Medicaid a less attractive option. If these transactions costs are non-zero, then some disutility is borne by participating in Medicaid.

Recent trends in Medicaid have shifted toward Medicaid managed care. For example, section 1115 waivers allow states to direct their Medicaid population into HMOs. In some cases, Medicaid participants are enrolled in commercial HMOs along

[24] See Table 5 for a summary of state outreach efforts.
[25] I choose not to say "mandatory" work requirements since there are many exceptions to the work requirement.

with privately insured patients (Welch & Wade, 1995). In addition, the Quality Assurance Reform Initiative (QARI) system, developed in 1991, helps to ensure that Medicaid recipients in managed care systems receive an improving quality of care (Felt-Lisk & St. Peter, 1997). Increasingly, there may be less disutility derived from participating in Medicaid. Throughout this analysis, the effect of a stigma and other transactions costs still apply.

Following Moffitt (1983), a woman's utility function, under Medicaid, is defined as the following:

$$\textbf{9. } \max_M U(H, D^{LT}, D^T, X) - \phi MCP \quad \textit{utility function}$$

where H reflects her infant's health, D^{LT} represents her long-term mental state, D^T reflects shorter episodes of depression, X is a composite commodity, ϕ reflects the stigma (and all transactions costs) associated with participation in a public program, MCP reflects Medicaid participation, and M is prenatal care. MCP equals one if the woman participates, and zero otherwise.

The health production function and production of depression are modified by the inclusion of Medicaid participation, MCP:

$$\textbf{10. } H = H(M, D^{LT}, Z^H, MCP) \quad \textit{health production function}$$

$$\textbf{11. } D^T = D^T(M, H, Z^D, D^{LT}, MCP) \quad \textit{transitory depression production function}$$

I assume that Medicaid participants receive lower quality medical care than privately insured individuals but perhaps higher quality care than the self-insured. This, however, should be left to an empirical question. Lower quality care may take many forms. For instance the high volume of patients that Medicaid providers treat may prevent them from

[26] However, some women are Medicaid eligible while they are not TANF eligible.

spending adequate time with each patient during a visit. As Welch and Wade (1995) illustrate, if Medicaid participants are less healthy than other individuals, then they may select into Medicaid since each of the frequent visits that they make is free (monetarily, at least). If a Medicaid provider is distracted by other health problems during these frequent visits made during the pregnancy, an extreme consequence of this may be that pregnancy complications go undiagnosed. Along the same lines, maternal depressive symptoms could also go undiagnosed, increasing the chances of post-partum depression. In addition, the provider pool of Medicaid providers is limited, restricting access to quality health care providers. Therefore, it is expected that Medicaid participation would lead to poorer infant health, ceteris paribus[27]. This is the first model that includes insurance or Medicaid participation into the infant health production function. As a result, this quality effect may be captured.

The budget constraint also changes to account for the price of Medicaid:

$$\textbf{12. } P^{MC}M + X = I \Rightarrow X = I - P^{MC}M \quad \textit{budget constraint}$$

where P^{MC} is the price of Medicaid prenatal care visit. I assume that this price is non-zero but minimal.[28]

Substituting in the constraints, the utility function becomes:

$$\textbf{13. } U\left(H(M, D^{LT}, Z^{H}, MCP), D^{LT}, D^{T}(M, H(M, D^{LT}, Z^{H}, MCP), Z^{D}, MCP), I - P^{MC}M\right) - \phi MCP$$

The first order condition is:

$$\textbf{14. } U_M = U_H H_M + U_{D^T} D_M^T + U_{D^T} D_H^T H_M - U_X P^{MC} = 0$$

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[27] However, as previously discussed, there is less of a distinction between a Medicaid provider and another provider as Medicaid participants move into commercial managed care. Under these circumstances, Medicaid may not lead to poorer infant health and mental health outcomes.

[28] If the price were zero, then an infinite amount of prenatal care could be demanded.

This condition is almost identical to the first order condition in the self-pay case, except for the price. An increase in the price of a Medicaid prenatal visit would have the same effect as an increase in the price of a self-paid visit. But if the price of a Medicaid visit is minimal (i.e. while there may be no dollar cost, there are transactions costs), then a woman would only need to forgo a small amount of her consumption of X, and face a minimal loss in utility, in order to maintain the same level of M.

The input demand equation or prenatal care can be written as a function of all of the exogenous variables in the system:

$$15.\ M^*(D^{LT}, Z^H, Z^D, P^{MC}, I, MCP, \phi)$$

Notice that in addition to price, income, and other exogenous variables, Medicaid participation affects the optimal level of prenatal care. The utility function is maximized by substituting in the optimized input demand equation, $M^*(.)$ and $D^{T*}(.)$, $H^*(.)$, and $X^*(.)$. The indirect utility function then becomes the following:

$$16.\ V^{MC}(D^{LT}, Z^H, Z^D, P^{MC}, I, MCP, \phi)$$

Private insurance case

The welfare stigma (and MCP) disappears in this model since it does not affect the utility of a woman that receives private insurance. However a safety net quality effect (γ) and private insurance participation variable (PI) are included in the model. Women with private insurance are likely to experience positive quality gains and the assurance of good health care. Additional terms are entered into the budget constraint to account for the premium paid on an insurance plan and in the utility function to account for the safety net that private insurance provides. In the private insurance case the price of prenatal care is the yearly premium, $prem$, plus the copayment, P^{PI}, paid at each visit. While the

copayment or P^{PI} is usually small (eg. $5), I assume that the premium is substantial. If it was not, more individuals would choose private insurance over Medicaid since it offers higher quality health care, better access to care, and there is no stigma attached. However, there would remain individuals who would not choose private insurance since private insurance is usually obtained through an employer. Not everyone would choose employment as a means to health insurance.

As substantial as they may be, premiums do vary across individual insurance plans. Individuals with employer-sponsored private insurance coverage are likely to pay smaller premiums than individuals without group coverage, yielding gains to employment. In addition, perhaps individuals who are associated with certain professions or unions may be offered less expensive and more comprehensive insurance plans than other workers[29]. Individuals that obtain that own health insurance are likely to pay exorbitant premiums.

Over time, it is expected that a closer relationship will form between certain aspects of private insurance and Medicaid. As Medicaid moves into commercial managed care, the entrance of less healthy Medicaid participants may place upward pressure on private insurance premiums. [Since my analysis is conducted with the 1988 "state of the world" in mind, HMOs, particularly Medicaid managed care is not relevant.] Welch and Wade (1995) find in their HMO study that controlling for age and sex, Medicaid participants are 23% more costly than privately insured participants are. Without controlling for these factors, Medicaid clients still cost 13% more. If the government does not reimburse HMOs at a higher rate (or a rate equal to at least 13%)

then other payers, HMOs will be forced to raise premiums to their other payers. Rising premiums have implications for both the private insurance and Medicaid populations. One substantial effect of higher premiums is that upon becoming eligible for Medicaid, some women may switch from private insurance to Medicaid. This is the crowding out phenomenon discussed by Cutler and Gruber (1996) and others.

The utility maximization problem in this case becomes:

$$17. \max_M U(H, D^{LT}, D^T, X) + \gamma PI \quad \textit{utility function}$$

and is subject to the production of infant health,

$$18. \; H = H(M, D^{LT}, Z^H, PI) \quad \textit{health production function}$$

the production of transitory depression,

$$19. \; D^T = D^T(M, H, Z^D, D^{LT}, PI) \quad \textit{transitory depression production function}$$

and a budget constraint,

$$20. \; P^{PI}M + prem + X = I \Rightarrow X = I - P^{PI}M - prem \qquad \textit{budget constraint},$$

where the price of the commodity is normalized to one. The modeling differences between this case and the case of self-pay are that the price per visit changes (or copayment), P^{PI}, a yearly premium, $prem$, is added to the budget constraint, and a quality effect (eg. safety net) effect, γ, and private insurance participation, PI, are included in the model. PI is assumed to have a quality effect on both the production of health and the production of depression. It is expected that higher quality care may be provided to women with private insurance coverage, thus providing a higher quality effect.

When the constraints are substituted in, the utility function becomes:

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[29] Later, in the empirical section, this is the justification for including the mother and father's industry and

$$21. U(H(M,D^{LT},Z^{H},PI),D^{LT},D^{T}(M,H(M,D^{LT},Z^{H},PI),Z^{D},PI),I - P^{PI}M - prem) + \gamma PI.$$

The first order condition is:

$$22. \; U_M = U_H H_M + U_{D^T} D_M^T + U_{D^T} D_H^T H_M - U_X P^{PI} = 0$$

This condition is also similar to the others except for the price.

Prenatal care can be written as a function of all of the exogenous variables in the system:

$$23. \; M^*(D^{LT},Z^{H},Z^{D},P^{PI},I,PI,\gamma,prem)$$

The utility function is maximized by substituting in the optimized input demand equation, $M^*(.)$, and the residually solved equations $D^T*(.)$, $H^*(.)$, and $X^*(.)$. The indirect utility function becomes:

$$24. \; V^{PI}(D^{LT},Z^{H},Z^{D},P^{PI},I,PI,\gamma I)$$

Now that the indirect utility functions have been derived, the utility that each yields can be compared.

Comparison of Cases

There are several differences among the three models, the most important being the monetary price per visit. I assume that:

$$25. \; P^{NO} > P^{PI} > P^{MC}; \; P^{PI}, P^{MC} \approx 0.$$

Holding the premium constant (equation **25**), the price of a self-paid visit greatly exceeds the price of a visit under private insurance or Medicaid. Without health insurance, some

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occupations as variables in the insurance, and therefore Medicaid, equations.

Americans cannot afford to seek appropriate medical care. However, in order to purchase private insurance a yearly premium, ***PI***, must be paid. When the premium is accounted for, private insurance becomes more expensive, though not necessarily more expensive than having no insurance. When private insurance is not employer-based, then privately insured prenatal care may become more expensive than uninsured care. This is why many Americans choose not to have private insurance - the opportunity cost is too high. According to price, prenatal care is most accessible to Medicaid participants.

Now consider the quality of care received under the three cases. I assume that:

$$\mathbf{26.}\ Q^{PI} > Q^{MC} >> Q^{NO};\ \phi > 0$$

The quality of care provided under private insurance is greater than that of Medicaid. (These two, however, are becoming increasingly closer in quality, particularly in the managed care population.) But for the reasons stated earlier in my analysis, the quality of care under Medicaid is expected to be inferior[30]. In addition, a non-zero stigma, ϕ, is associated with Medicaid participation, reducing the attractiveness of Medicaid. The quality of care received by a woman who is not insured is likely to be of much less quality than the other two. Recall that physicians regard these individuals as "bad debt". It is not worth their time to provide quality care to a potentially non-paying patient. In addition, it is unlikely that these patients even have access to higher quality providers. In terms of quality, a woman is more likely to choose private insurance, or secondly, Medicaid.

A woman ultimately chooses her health insurance coverage by the type that maximizes her utility. A comparison of indirect utility functions illustrates these choices.

Pair-wise comparisons of the three insurance cases are made here in order to illustrate why one type of coverage is preferred to another. However, I assume that a woman chooses only one of the three possible insurance types yielding:

$$27.\ V^* = \max[V^{NO}, V^{PI}, V^{MC}]$$

The first set of choices to consider is whether having no insurance or participating in Medicaid yields a higher level of utility:

$$28.\ V^{NO}(D^{LT}, Z^H, Z^D, P^{NO}, I) \quad v. \quad V^{MC}(D^{LT}, Z^H, Z^D, P^{MC}, I, MCP, \phi).$$

Four of the primary factors that affect this choice are the quality and frequency of care, the welfare stigma (ϕ), and knowledge about Medicaid eligibility. I assume women who are uninsured obtain fewer, lower quality visits while Medicaid participants receive many, higher (but not necessarily high) quality visits. That is, since the price of an uninsured visit greatly exceeds the price of a Medicaid visit ($P^{NO} >> P^{MC}$) to the extent that the price of a Medicaid visit is free (holding aside transportation and other transactions costs) uninsured women are likely to demand fewer prenatal visits. If the frequency of visits is highly valued (where more is better), a woman may choose to participate in Medicaid ($V^{MC} > V^{NO}$). In addition, Medicaid provides higher quality visits. In this case, women may desire Medicaid ($V^{MC} > V^{NO}$).

On the other hand, particularly with the Medicaid expansions that occurred over the past decade, many women do not have knowledge of their Medicaid eligibility.

Therefore, imperfect information may encourage a woman to believe that she i s better off paying for her own prenatal care ($V^{NO} > V^{MC}$). Additionally, the perception of a welfare stigma (ϕ) may reduce the likelihood of Medicaid participation. The welfare stigma acts as a fixed cost to Medicaid participation. A woman must face or accept this stigma prior to participation. If a woman perceives this fixed cost to be too high, then she may choose to go uninsured ($V^{NO} > V^{MC}$).

The second set of choices to consider is whether having no insurance or purchasing private insurance yields a higher level of utility:

$$29.\ V^{NO}(D^{LT}, Z^{H}, Z^{D}, P^{NO}, I) \quad v. \quad V^{PI}(D^{LT}, Z^{H}, Z^{D}, P^{PI}, I, PI, \gamma, prem).$$

The three primary factors that affect this choice are the price of a private insurance premium (PI), the price of a prenatal visit (P^{PI} and P^{NO}), and the quality of care provided. While private insurance provides frequent, high quality prenatal care, private insurance premiums are usually substantial in price. If a woman is not willing to pay this fixed cost, she may forgo insurance ($V^{NO} > V^{PI}$). Additionally, gainful employment is often a means of obtaining private health insurance. If a woman feels the opportunity cost of working is too high, she would likely choose not to be insured ($V^{NO} > V^{PI}$). However, not all premiums are the same. Typically, employer-sponsored or group insurance premiums are less than individual premiums, reducing the price a woman faces. In this case, a woman may be willing to pay for private insurance ($V^{PI} > V^{NO}$). In addition, the price of a prenatal visit is lower for insured women than for uninsured women ($P^{PI} < P^{NO}$). This suggests that insured women obtain more prenatal visits than uninsured women do. If frequency of visits is desired, a woman may choose to be insured ($V^{PI} > V^{NO}$). Finally, the quality of care provided to insured individuals is assumed to be substantially higher than the quality

provided to the uninsured. Clearly, if quality is desired, a woman chooses to be insured ($V^{PI} > V^{NO}$).

The third set of choices to consider is whether participating in Medicaid or purchasing private insurance yield a higher level of utility:

30. $V^{MC}(D^{LT}, Z^{H}, Z^{D}, P^{MC}, I, \phi, MCP)$ *v.* $V^{PI}(D^{LT}, Z^{H}, Z^{D}, P^{PI}, I, PI, \gamma, prem)$.

The four primary factors that affect this choice are the level of health care quality desired (*MCP*,*PI*), the welfare stigma and safety net (ϕ, γ), the relative prices (P^{PI} and P^{MC}), and the fixed cost of a private insurance premium (*PI*). In both cases, a woman is likely to obtain a frequent schedule of visits, although the price of a Medicaid visit is less than an insured visit. If she values high quality care and is willing to pay expensive insurance premiums, she chooses to be privately insured ($V^{PI} > V^{MC}$). If she is willing to forgo the higher quality care provided under private insurance and accepts a reasonable quality of care and the welfare stigma, then she chooses to participate in Medicaid ($V^{MC} > V^{PI}$).

Recall that this case provides an interesting policy implication. Several studies discussed earlier find that when Medicaid income eligibility is expanded, some women drop their private insurance in lieu of Medicaid. That is, Medicaid crowds out private insurance. However, crowding out presumes that either not all women are eligible for Medicaid from the start or that they have no knowledge of their eligibility. The theoretical framework does address crowding out to the extent that it assumes all women are Medicaid eligible. The empirical model takes into account that eligibility is exogenous, while still allowing women to freely select into Medicaid. The policy

simulations reveal that expanding Medicaid eligibility may increase the probability that a woman participates in Medicaid and nowhere is Medicaid forced upon an individual. Additionally, the policy simulations make a gross estimation of crowding out.

On one last note, the framework implies that all three cases (private insurance, Medicaid, and no insurance) are viable options for all women. Despite the Medicaid income eligibility expansions during the past decade, millions of American women have family incomes that lie above the eligibility threshold, making them ineligible for Medicaid, but making it difficult to purchase private insurance. It is perhaps a moral question whether it is right to assume that any woman has the free choice to reduce her income in order to become eligible for Medicaid or to secure employment with benefits. This moral question will not be answered here.

General Description of Data

The primary data set used in this dissertation, National Maternal and Infant Health Survey, 1988 (NMIHS), is publicly accessible data published by the National Center for Health Statistics (NCHS). This data set has been used in a number of similar studies that evaluate the correlates of prenatal care, substance abuse, and birth weight (for example, Warner, 1998; Hanna, Faden, & Dufour, 1994). NMIHS contains information on 26,355 women who were pregnant in 1988 and experienced a live birth, infant death or fetal death. Only data on the sample of women that experienced a live birth are used in the estimation process (except the first stage - see sample selection discussion). Additional outliers (discussed later) are also eliminated and the data are stratified to reflect the differences between black and white mothers. Questions asked during the interview

concerned prenatal care and health habits, delivery of the baby, insurance and Medicaid coverage, previous and subsequent pregnancies, socioeconomic characteristics of the mother and father, and infant health. In order to ensure confidentiality of the women in the NMIHS, NCHS "has removed identifiers and characteristics that might lead to identification of data subjects".

While the NMIHS sample generally reflects pregnancies throughout the U.S. there are a few caveats. The NMIHS is divided into three cohorts: the infant death cohort, the fetal death cohort, and the live birth cohort. In the analysis, I only use the live birth cohort[31]. In the live birth cohort, both blacks and poor birth outcomes are oversampled. This may create a potential bias since the data more likely reflects the characteristics of blacks (proportionally) and poor birth outcomes. Since all of the empirical models are stratified by race, black oversampling no longer presents an issue. Oversampling of poor outcomes may provide more insight as to the correlates of low birth weight - one focus of this dissertation. This suggests that weighted regressions may not be appropriate here. However when weighted means for the key variables are computed, they are almost identical to the unweighted means. Therefore, none of the empirical procedures use weighted data.

For certain estimation procedures and variables, several other data sets are used. The National Longitudinal Survey of Youth (NLSY) is sponsored by the Bureau of Labor Statistics (BLS), U.S. Department of Labor and contains information on 12,686 women and men on a wide range of topics. This data source is used to correct for the sample

selection issue in the first stage of estimation. BLS requires a statement ensuring that I protect the confidentiality of the subjects in the data set. The NMIHS 1991 Follow-up is used to collect a second observation on depression in order to create a long-term depression measure. The American Chamber of Commerce Researchers Association Cost of Living Index (ACCRA) includes price data from 256 U.S. cities on health care, grocery items, housing, utilities, transportation and other goods and services. This data is used to capture environmental characteristics. Since only a woman's state of residence (not city) is identified in the NMIHS, I aggregate the city data into state data by averaging the city data. Additional state level information is taken from the Statistical Abstracts of the United States and the US Census Bureau Web Site. Finally, in order to perform policy simulations, several other variables are used. These include state-level Medicaid eligibility guidelines for several years in the 1980s and 1990s and the federal poverty guidelines from 1988-1999. These data elements are taken from several sources including U.S. Department of Health and Human Services Annual update of the HHS poverty guidelines.

Data Description

This section provides a detailed description of the key variables (prenatal care, depression, and birth weight) in the empirical model as well as some simple descriptive statistics. A general description of all of the variables used in the analysis appears in **Table 8**. Simple descriptive statistics on all of the variables, stratified by race, and

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[31] Both the fetal and infant death cohorts oversample blacks and Hispanics. In addition, the fetal death cohort does not include any terminations less than 28 weeks. This means that only miscarriages are included but no abortions are included. As a result, the NLSY is used as an alternative sample for the initial

broken down by the full sample (all births) and the sample of term births appear in **Tables 9** and **10**.

Discussion of outliers

The National Maternal and Infant Health Survey, 1988 (NMIHS) surveys more than 26,000 women on a variety of topics. Initially removed from the data are infant and fetal deaths and multiple births, reducing the sample to 9146 women. Infant and fetal deaths are removed (leaving only live births) since the analysis primarily focuses on infant health. Live multiple births (twins, etc.) are eliminated since these infants tend be born at shorter gestation and of lower birth weight, thus biasing the data.

In addition, as one would expect with survey data, there is missing data and anomalies in the data in several of the data fields. The following categories of outliers are removed from the 9146 observations of the NMIHS data:

- Missing or invalid data
- Women with no prenatal care[32] (N=284)
- 119 women are recorded as having both private insurance and Medicaid. This overlap is likely due to the way in which the insurance questions are asked. Since I cannot accurately categorize these women, I eliminate them from the sample.
- Birth weights below 400 grams (.88 lbs.) or above 6000 grams (13.23 lbs.). This follows Warner (1998) who also used the NMIHS.
- Gestation less than 20 weeks or more than 45 weeks. This also follows Warner (1998).

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stage of estimation since abortions are included in that sample.

[32] It is not entirely clear how the literature addresses this issue. However, since the percentage of women with no prenatal care is small, these are eliminated from the analysis.

The final sample of all births is 5121 observations. The full sample of all white births is 2562 observations while the full sample of all black births is 2106 observations[33]. Observations on women with no prenatal care do not appear in the final sample. Prior to removing the outliers discussed above, when the sample was 9146 observations, 284 women or 3.1% of that sample had used no prenatal care. However, once the additional outliers were removed and the total sample became 5121 observations, all women that remained had at least one prenatal visit. Therefore, women with no prenatal care were not actually removed from the sample but did not appear in the final sample.

Part of the analysis requires that the sample be controlled for gestation (where only births that were of full gestation or greater than 37 weeks are included). The full term sample of white births includes 2084 observations while the full term sample of black births includes 1677 observations.

Discussion of prenatal care measures

The difficulty in choosing the "best" prenatal care measure to use in this dissertation is that there is no accepted "standard" for measuring prenatal care (Alexander and Kotelchuck, 1996). **Table 3** illustrates a number of different ways that prenatal care is measured in the literature. These include straightforward measures such as the onset (or delay) of prenatal care and the number of prenatal visits to a variety of indices that account for gestation and adequacy of care. Of all the measures, the onset (or delay) of prenatal care is the most widely used (see **Table 3**) and the least criticized, since the majority (if not all) of health care providers believe that early prenatal care is the key to a

[33] 5121 (full sample) - 2562 (white sample) - 2106 (black sample) = 453 women of other races that are excluded from the analysis.

healthy pregnancy[34]. On the other hand, the number of prenatal visits obtained, some argue, does not accurately reflect the healthiness of a pregnancy. The Public Health Service maintains that women with little risk of pregnancy complications do not require as many prenatal visits as women who are at higher risk (Binstock & Wolde-Tsadik, 1995; Witwer, 1990). They find that infants born to (healthy) mothers who are on a reduced schedule of prenatal visits are just as healthy as those born to mothers on a more traditional schedule are.

Prenatal care indices have been criticized by some since they do not accurately reflect the content of care provided nor the barriers to care (Mahan, 1996). Alexander and Kotelchuck (1996) shed some light on the different types and usefulness of prenatal care indices found in the literature. Each one of these indices is defined in **Table 3**. In general, they find that each index employs a different approach to utilization, and are thus, incomparable. While they don't recommend any one as the "standard", they make suggestions on how each can best be used.

The Kessner or Institute of Medicine (IOM) index was the first prenatal care index developed and as a result, is the most widely used index. This index takes into account the onset of prenatal care, the number of visits obtained, and whether the infant was delivered by a private obstetric service. Both the American College of Obstetrics and Gynecology (ACOG) and the Public Health Service's Expert Panel on Prenatal Care suggest guidelines for an "adequate" schedule of prenatal care. Alexander and Kotelchuck (1996) argue that the Kessner Index does not appropriately take into account these guidelines and consequently classifies too many women as receiving adequate

[34] According to ACOG and the Public Health Service.

prenatal care. They recommend that this and similar indices should no longer be used. The OB-Rec Index modifies the Kessner Index by more accurately reflecting the ACOG recommendations. However this index does not measure intensive use of prenatal care. Women that utilize "a lot" of prenatal care tend to have poorer birth outcomes. Therefore, the authors recommend that the OB-Rec Index should not be used in research that evaluates the relationship between prenatal care and birth outcomes.

Three additional indices are also discussed. The PHS-Rec is based on the Public Health Services' recommendations for prenatal care. Recall from the earlier discussion that they recommend that prenatal care begin as early as during the pre-conception period. They also argue that the amount of prenatal care recommended should be a function of complication risk. Alexander and Kotelchuck are hesitant about using the PHS-Rec since the proposed pattern of visits is not widely recommended to patients in the U.S. However, this index may be useful in comparative studies of proposed prenatal care practice standards (p. 414). The GINDEX uses similar categories to the Kessner Index but also includes categories for missing data, no prenatal care, and intensive prenatal care. This index also more accurately reflects the ACOG recommendations. The authors find this index useful for birth outcomes research and in monitoring intensive use of prenatal care. Finally, the APNCU Index uses similar categories to the GINDEX but is less restrictive about assigning women to the intensive use category. This index also separates the onset of prenatal care from compliance of visit recommendations. As a result, the authors find the APNCU Index useful in assessing prenatal care utilization especially after care is initiated.

Based on this research, I use two measures of prenatal care: the onset (***Onset***) of prenatal care in weeks and the actual number of visits divided by the ACOG recommended number of visits (***ACOGadj***), controlling for gestation. The first measure is widely used within the context of the health production function framework (Rosenzweig and Schultz, 1982, 1983; Warner, 1995, 1998; Grossman and Joyce, 1990; Joyce and Grossman, 1990). The second measure not only takes into account the ACOG recommendations, but also reflects intensive prenatal care use. **Appendix 1** provides the ACOG recommended number of prenatal care visits and the derivation of this measure of prenatal care. **Figures 2** and **3** illustrate the distribution of the onset of prenatal care (in weeks) for white and black women. **Figures 4** and **5** show the distribution for white and black women of the ACOG adjusted visit measure (i.e. the actual number of visits divided by the ACOG recommended number of visits, controlling for gestation). Means of other key variables stratified by prenatal care category can be found in **Table 11**.

Discussion of CES-D as a measure of depression

Depression is measured by the Center for Epidemiological Studies Depression (CES-D) Scale. This scale was developed in 1969 as part of the Community Mental Health Assessment (CMHA) program that was conducted by the Center for Epidemiological Studies (CES), National Institute of Mental Health (NIMH). It was developed to identify the presence and severity of depressive symptomatology in the general population. However, it was not intended to discriminate among different types of depression nor to distinguish primary depressive disorders from secondary depression (Radloff & Locke, 1986). This is the downside of using the CES-D to capture long-term and transitory depression.

The CES-D scale is a self-reported survey consisting of 20 questions concerning depressed mood, feelings of guilt, worthlessness, helplessness, and hopelessness, psychomotor retardation, loss of appetite, and sleep disturbance. The specific questions asked appear in **Table 12**. The responses reflect the frequency of symptoms experienced by the respondent during the past week. Each response is scored from 0 to 3 based on the frequency of the occurrence, yielding a range of 0-60, with higher scores reflecting more depressive symptoms. Four questions regarding positive feelings and emotions are included to break tendencies toward negative feelings. The literature (Locke et al., 1997; Zimmerman & Coryell, 1994; Radloff & Locke, 1986; Roberts & Vernon, 1983) has consistently used a score of 16 (and greater) as the cutoff to indicate depression. The CMHA found that these scores are correlated with the presence of clinical depression diagnosed by a psychologist (Radloff & Locke, 1986). **Figures 6** and **7** illustrate the distribution of CES-D scores by race and the means of other key variables for depressed and non-depressed women are in **Table 13**.

The CES-D scale is only one of 30 symptom checklists (scales) that measure some aspect of depression and depressive symptoms (Snaith, 1993). It is one of the most frequently used instruments to identify cases in a community sample (Zimmerman & Coryell, 1994; Melchior, Huba, Brown, & Reback, 1993). Several studies have evaluated the validity of the CES-D scale with respect to more intensive clinical assessments of depression. In general, the research seems to suggest that symptom checklists should be used as an initial screening of patients. Roberts and Vernon (1983) summarize these studies of the CES-D scale. They find that the scale is internally consistent and has acceptable re-test stability. In addition, the scale has good construct validity in clinical

and community samples and is reasonably good at screening out non-depressed patients. However, the CES-D scale suffers from a number of shortcomings. The first is that only a modest relationship exists between this scale and more clinical diagnoses such as the RDC (Research Diagnostic Criteria). Secondly, the scale is more sensitive to current symptoms rather than lifetime RDC diagnosis of depressive illness. Finally, the CES-D scale identifies diagnoses other than depression including psychological distress common to various types of psychiatric disorders. This may be due to the composition of questions in the instrument. Some argue that many of the items in the scale do not reflect the DSM-III (3rd edition of the Diagnostic and Statistical Manual of Mental Disorders) criteria for major depressive disorder (Zimmerman & Coryell 1994).

The shortcomings of this measure should not dissuade its use in this dissertation. It is only used in this dissertation to roughly assess a woman's state of mental health and the incidence of depressive symptoms. However, in my data set, the timing of when the CES-D scale is assessed in a concern. On average, this measure was taken 17 months after the delivery. This means that not only is the scale capturing long-term depression, but it may also capture post-partum depression. Post-partum depression is not to be mistaken with the "baby blues"[35]. Post-partum depression (non-psychotic) occurs in 10%-15% of all women, with the onset beginning 6 weeks to one year following birth and lasting for 6-8 weeks, on average (Downey, 1996). For some women, particularly ones whose interview was conducted less than one year following childbirth, the CES-D scale

[35] At least 70% of women suffer from a short spell of depression or indifference called the baby blues with the first month following childbirth. It usually lasts for only a few days. Downey, J.I. (1996). Recognizing the range of mood disorders of women. Medscape Women's Health, 1(8) [Online]. Available: http://www.medscape.com/Medscape/WomensHealth/journal/1996/v01.n08/w159.downey/w159.downey.html#Pregnancy

potentially captures post-partum depression. In general, the scale captures both the long-term exogenous component and the transitory endogenous component (such as post-partum) of depression. To better capture the long-term component of depression, the CES-D scale measure taken during the 1988 survey is augmented with a CES-D scale measure taken during a 1991 follow-up survey (the NMIHS, 1991) of the same women. There is some evidence that women who are depressed following childbirth maintain their symptoms even two years later (Small, Astbury, Brown, & Lumley, 1994). Therefore, a simple average[36] of the CES-D scores taken during the 1988 survey and the 1991 survey are used as a better measure of long-term depression.[37] A more ideal measure of long-term depression would be taken before the pregnancy began, but is not available in this data set.

The transitory component of depression is eliminated from the empirical model. This type of depression is more likely an output of the production (of infant health) process, rather than an input. The original intent behind incorporating depression into the framework was to evaluate its effect on prenatal care and infant health. As was just discussed, the transitory measure alone ($CES\text{-}D^{1988}$) is not a good predictor of this. In addition, incorporation of the transitory component requires estimation of a depression equation since it is an endogenous variable. A depression equation is not estimated. The empirical model focuses on the long-term component. A more detailed discussion of this appears in the empirical model section.

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[36] $\frac{CESD^{1988} + CESD^{1991}}{2}$

[37] Using the 1991 measure alone may be problematic as well. If a woman became pregnant around 1991, then the 1991 depression measure may capture an episode of post-partum depression or some other type of transitory depression.

Discussion of birth weight measures[38]

Table 2 illustrates different measures of infant health found in the literature. Birth weight is the most commonly used measure of infant health, especially in health production function studies (including Grossman & Joyce, 1990; Rosenzweig & Schultz, 1982, 1983; and others). While neonatal and infant mortality rates are another common output of the health production function (Corman, Joyce, & Grossman, 1987; Corman & Grossman, 1985) I choose not to use these measures for several reasons. Most studies that use these measures use aggregate measures of mortality expressed in deaths per 1000. Most micro-level data sets do not contain enough observations on infant deaths. Although the NMIHS contains several thousand observations on infant deaths, it is unlikely that I could compare my results to similar studies (since they would not exist). Additionally, these are extreme measures of the lack of infant health. For these reasons, I rule out the use of mortality rates as sufficient measures of infant health.

Gestation is yet another measure of infant health used in similar studies (see **Table 2**). The problem with using gestation is that it suffers from measurement error (Rosenzweig and Wolpin, 1991). Gestation is the number of weeks that the pregnancy lasts. Computing this not only requires knowledge of the delivery date but also the date of conception. Often, it is difficult to pinpoint this date. Consistent with the literature, birth weight and birth weight controlled for gestation are used as two different measures of infant health.

Dichotomous measures of low birth weight (less than 2500 grams/5.51 lbs.), term low birth weight (less than 2500 grams but greater than 37 weeks gestation), very low

[38] 1 pound = 453.6 grams

birth weight (less than 1500 grams/3.31 lbs.), and extremely low birth weight (less than 750 grams) are measures of infant health also found in the literature (Joyce, 1997[39]). It is well established that low birth weight is the primary determinant of infant mortality, especially in the neonatal[40] period (McCormick, 1985). Rogowski (1998) finds that despite advances in neonatal technology, the treatment costs to keep an infant weighing less than 750 grams (at birth) alive until her first birthday are five times higher ($273,900 v. $58,000) than one weighing 1250-1499 grams (at birth). The author states that any prenatal intervention that results in a normal birth weight can save thousands of dollars in medical costs. The model proposed in this dissertation is suitable to evaluate the contributors to very low birth weight. However, other studies argue that either little can be effectively done to prevent preterm birth, including increasing access to prenatal care, or that little is known about preterm delivery (Ray, Mitchel, & Piper, 1997; Piper, Mitchel, Ray, 1996a; Collaborative Group on Preterm Birth Prevention, 1993). Therefore, an economic model would not uncover any meaningful results. Since the research to date remains mixed, it seems reasonable to empirically evaluate the question. In addition to using health outcomes (such as birth weight) that apply to the more general population, a special study on low birth weight infants is conducted in this dissertation. In my model, I use the following four different measures of birth weight: birth weight in grams, term birth weights, a dummy variable indicating low birth weight, and a dummy variable indicating term low birth weight. I actually define two different samples in the analysis: a sample including all births (where I use the birth weight and low birth weight measures) and a sample only using full term births or births of gestations greater than 37

[39] Except less than 750 grams

weeks (where I use the term birth weight and term low birth weight measures). Key variable means stratified by low birth weight and normal birth weight can be found in **Table 14**.

Descriptive Statistics Discussion

Table 11 illustrates the differences in means of important variables in the model, according to the time at which the woman first sought prenatal care. In general, the health care industry encourages women to seek prenatal care as early as possible, or more generally during the first trimester (first 1/3 of the pregnancy). The results from this table indicate that, for both whites and blacks, women who began prenatal care during the first trimester (versus women who began later) have higher birth weight infants, a lower depression score, are more likely to have private insurance and less likely to have Medicaid, are older, more educated, and are far more likely to have been married at some point. In general, these results demonstrate that there are many factors that are correlated with seeking early prenatal care.

Table 13 reflects differences between women who are considered depressed (CES-D >= 16) and women who are considered not to be depressed (C-ESD < 16). The results indicate significant differences in the behavior of depressed and non-depressed women. Women who are depressed tend to seek prenatal care later, are younger, less likely to be married, and are less educated than non-depressed women. This is not a surprising result. Additionally, depressed women have lower birth weight infants than non-depressed women do. This provides some evidence that depressed women may pass on their depressed state, in some form, to their infants. Depressed women are also more

[40] Neonatal is considered the time from birth to 27 days after birth.

likely to participate in Medicaid and are less likely to have private insurance. One explanation for this is that depressed women may be less likely to secure employment, having less access to private insurance. In addition, it is possible that women who reveal that they are not depressed have been treated for depression. The higher incidence of non-depressed people with private insurance may indicate that private insurance is better at treating depression than Medicaid. All of these results hold true for both black and white women. The one difference is that depressed women who are white seek more visits while depressed women who are black seek significantly fewer visits. The explanation for seeking more visits may be due to a state of confusion or paranoia that may be associated with depressed. On the other hand, it seems just as likely that depressed women have difficulty seeking care since research has shown that depressed individuals have more difficulty functioning than non-depressed individuals. Thus, it is also likely that there are confounding effects at work here.

The most striking result in **Table 14** is that both white and black women who have low birth weight infants seek over 40% more visits than women who have normal weight infants. Realize that these visits are adjusted for gestation. This result seems to indicate that women may be aware of pregnancy complications that result in either pre-term delivery or a low birth weight infant. In addition, white women with low birth weight children seek prenatal care earlier than women with normal birth weight children. These results further support the explanation above. If a problematic pregnancy is expected, a woman seeks prenatal care early. However, black women behave in an opposite way. This suggests that pregnancy complications may have not been caught early enough (due to the later onset of care) and resulted in a low birth weight infant. The

other results indicate that women with lower birth weight infants are younger, less educated, more depressed, less likely to be married, more likely to participate in Medicaid, and less likely to have private insurance.

Implementing the Empirical Model

Correcting for sample selection created by using the live birth sample

In implementing the empirical model I face a number of statistical hurdles. Sample selection - one type of selectivity bias - is one common problem that researchers face when data on the endogenous variable is missing in a systematic manner (Maddala 1985). Specifically, the sample that I use to estimate the model includes only women who experienced a live birth. This sample is not representative of all pregnant women. A sample of all pregnant women would include those who experience a variety of outcomes including live birth, fetal death, abortion, or infant death. According to Joyce and Grossman (1990) one might expect that the behavior of women in the former group might differ from those in the latter group. For example, women that experienced a live birth may be healthier or may have desired their child more, resulting in demanding more frequent and timely prenatal care, on average, than women who experienced an abortion or other fetal/infant death. This means that the onset of prenatal care in the live birth sample would be a misleading indicator of the onset of prenatal care by all pregnant

women. Joyce and Grossman propose that in order to correct this sample selection issue, Heckman's two-step (Heckman 1979) procedure is employed[41].

Following Greene (1993), suppose that prenatal visit demand (M) and the incidence of a live birth (B), have a bivariate distribution with correlation ρ, such that:

$$\rho = \frac{cov(M,B)}{\sigma_M \sigma_B}, \quad \rho > 0, \quad \sigma_i > 0, \quad i = M, B$$

If M and B are positively correlated ($\rho > 0$) the truncation of B (elimination of pregnant women who do not experience a live birth) should push the distribution of M to the right. What this means is that the mean and variance of M (number of prenatal visits) are unobserved; however, the mean and variance of M *given* that $B > a$ (where $B = 1$ or that the woman experiences a live birth) is observed. Intuitively, this says that the truncated mean of M given by $E[M \mid B > a]$ is pushed in the direction of the correlation - which is assumed to be positive. In addition, the truncated variance of M given by $Var[M \mid B > a]$ is heteroskedastic.

There are a number of solutions in the econometrics literature to correct for such sample selection. Following Joyce and Grossman (1990), I employ Heckman's two-step procedure. Greene (1993) describes this procedure in detail. The first step is to estimate a probit model on the probability that a woman experiences a live birth (i.e. prob ($B = 1$)). The second step requires using the parameter estimates, b, to construct an inverse Mills

[41] The abortion literature is relevant here. Some research indicates that restricting the availability of abortion services reduces the average birth weight. Currie, Nixon, and Cole (1996) find that restricting the Medicaid funding of abortion increases the probability of a live birth among women who did not want the pregnancy. It is expected that these women are more likely to have adverse infant health outcomes since they did not want the pregnancy in the first place. Given this, it is necessary to control for this effect.

ratio, λ. The inverse Mills ratio is included as a regressor in subsequent equations of interest to account for the bias which results from sample selection.[42] The inverse Mills ratio equals the probability density function divided by one minus the cumulative density function:

$$\lambda(b'x) = \frac{\phi(b'x)}{1 - \Phi(b'x)}$$

In order to perform this statistical procedure, it is necessary to have data on a sample of all pregnant women. From this, a variable can be created that weights the sample of women that experienced a live birth so that inferences can be made about the entire pregnant population. In reading the fine print in the data documentation of the NMIHS, it was discovered that this data set does not contain observations on all pregnant women. It contains observations on women that experienced a live birth, an infant death (i.e. death soon after birth), and fetal deaths that occurred more than 28 weeks into the pregnancy. Abortions are not included. Therefore, in order to perform Heckman's two-step procedure, abortion data needed to be collected.

Angrist and Krueger (1992, 1995) derive a two-sample instrumental variables (IV) approach that is applicable to Heckman's two-step procedure but utilizes two different data sets. Two-sample IV was motivated by the fact that even large samples may not

[42] The heteroskedasticity caused by self-selection is corrected by using White standard errors.

always include an exhaustive set of important variables of interest. In order to conduct a two-sample, Heckman's two-step procedure, another data set that contained the exact same variables as the NMIHS but with data on all pregnancies had to be located. The NLSY was chosen as this data source. Refer to the NLSY as data set one and the NMIHS as data set two. The two-sample, two-step procedure is performed as follows:

Step One: Recall that in step one of the two-step procedure, a probit is estimated on the probability of experiencing a live birth. In the two-sample approach, the NLSY data (represented by the subscript one) is used to estimate this probit. Next, the parameter estimates obtained from this probit are multiplied by the data (exact same variables) from the NMIHS (represented by subscript two). This creates a predicted value of the probability of experiencing a live birth using data from the NMIHS and the parameter estimates from the NLSY.

Step Two: Now, the inverse Mills ratio is computed using the formula:

$$\hat{\lambda}(b_1' x_2) = \frac{\phi(b_1' x_2)}{1 - \Phi(b_1' x_2)}$$

Finally, $\hat{\lambda}$ is included as a regressor in all successive estimation procedures to correct for sample selection and $b_1'x_2$ can used to correct for heteroskedasticity.

Correcting for heteroskedasticity

It has been alluded to that heteroskedasticity is likely to persist throughout the treatment effects model. Generally any selection bias is likely to cause heteroskedasticity. In this model, there are multiple selection issues that must be taken into account including selecting into the live birth population and the Medicaid and private insurance

populations. Additionally, cross-sectional data also presents the possibility of heteroskedasticity. Two alternative methods for appropriately dealing with heteroskedasticity is to either build it into the model using Generalized Least-Squares (GLS) or to adjust the standard errors. Since I suspect that one or more forms of heteroskedasticity may be present throughout the model, I adjust the standard errors for general heteroskedasticity in a manner similar to White (1980).

Endogenizing Medicaid and private insurance

Incorporating insurance into the framework presents another statistical, yet interesting issue. Clearly, insurance is a choice variable, particularly for pregnant women. (However, eligibility rules are assumed to be exogenous). On the one hand, if a woman expects to become pregnant, she is more likely to seek out adequate health insurance. This can be in the form of private insurance or Medicaid. In many cases, pregnant women are eligible to receive Medicaid. But, on the other hand, not all women that are eligible to receive Medicaid participate and some women that become Medicaid eligible drop their private insurance in lieu of Medicaid[43].

This presents a classic case of an endogenous explanatory variable - a variable whose value is determined within the system. One way to statistically correct for this issue is to employ the instrumental variables approach. Conceptually, this means that insurance is regressed across all of the explanatory variables in the system, from which a predicted value of insurance is produced. This predicted probability of having insurance is then included as a regressor in subsequent equations of interest. While this approach is

statistically sound, the downside of using this approach is that the predicted probability is a function of the latent variable, not the discrete one. A parameter estimate would only illustrate the effect of the predicted probability of having Medicaid or insurance on birth weight, for example. Ideally, one would prefer to know the direct effect of actually having private insurance or Medicaid on prenatal care and birth weight. In light of this, an alternative correction is used to mitigate the endogeneity problem. The approach used is called the treatment effects model.

According to Maddala (1983) one of the major uses of self-selection models is to evaluate the effect of a social program. The treatment effects model is one type of self-selection model. This model presumes that individuals that participate in a social program, such as Medicaid, select into the program in anticipation of reaping benefits that they would otherwise not get. It is expected that the individuals that self select into the program will reap greater benefits from the program than a randomly assigned group that participates. This can also be applied to private insurance. Individuals who choose to have private insurance coverage do so since the expected benefit is greater than it would be for a randomly assigned group. This is called self-selection[44]. The theoretical framework models this self-selection by allowing a woman to choose the type of insurance coverage that maximizes her utility. The treatment effect model is econometrically appropriate, follows the theoretical model, and allows for the parameter estimates on Medicaid and insurance to be directly interpreted.

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[43] This is discussed in much greater detail in a later section.

[44] Another common application of this model, discussed in Greene (1993), is used to describe the effect of a college education on earnings.

Simply put, the treatment effects model is similar to Heckman's two-step procedure. A probit is estimated on whether or not a woman participates in Medicaid. From the predicted probability generated, an inverse Mills ratio is constructed and included as a regressor in subsequent equations of interest. However, in addition, the treatment effects model also includes the actual Medicaid dummy variable as a regressor. Therefore, the final model would not only include $\beta_1\lambda$, the inverse Mills ratio, but it would also include β_2 *Medicaid*, the Medicaid dummy variable. Note though, that both a dummy variable indicating the presence of Medicaid and the Mills ratio must be included in the model in order to evaluate the individual effect of Medicaid[45]. The next section discusses in detail how these two equations are estimated.

Empirical model

The goal of this estimation procedure is to evaluate the interaction between depression, prenatal care and birth weight, paying close attention to the effect that private insurance and Medicaid have on this system. Conceptually, three stages of estimation take place, with reduced-form equations estimated in all stages except for the birth weight equation that is estimated structurally. Refer to **Figure 8** for an overview of these three stages. The initial stage corrects for the sample selection bias that is caused by a sample of women that experience a live birth. The second stage corrects for the sample selection (or endogeneity) bias caused by participation in Medicaid or private insurance. These first two stages are necessary in order to produce consistent estimates in the final stage. The final stage estimates the model of interest. A structural-form birth weight equation

[45] An identical process is conducted for private insurance.

and a semi reduced-form prenatal care equation are estimated using a recursive treatment effects model. Although depression is included as an exogenous regressor in the model, a depression equation is not estimated for the reasons discussed below. Since many of the variables are expected to systematically differ by race, the entire analysis is stratified by race. White and black samples are carried through the analysis. The stages of estimation are discussed in similar order to the theoretical model.

Initial Stage

The purpose of this stage is solely to correct for the sample selection bias that is created by using a subset of the data. In stage one, a probit[46] is estimated on the probability that a woman experiences a live birth. The dependent variable, ***Live Birth*** is a binary variable equal to one if the woman experienced a live birth and zero otherwise. The reduced-form probit is defined as the following:

$$1.\ \textit{Live Birth} = \psi_1 + \psi_2 \textit{wanted} + \psi_3 \textit{age} + \psi_4 \textit{income} + \psi_5 \textit{black} + \psi_6 \textit{white} + \psi_7 \textit{high school} + \psi_8 \textit{college} + \psi_9 \textit{marital} + \varepsilon^{LIVE}$$

One may notice that while this equation is a reduced-form equation, it is missing many of the exogenous variables in the system. This is a consequence of mapping the NLSY data to the NMIHS data - the variables must be matched identically in the two data sets. The NLSY does not contain the full set of exogenous variables in the system. Only the

[46] For the following reason, a probit is estimated when the dependent variable is binary - if ordinary least-squares (OLS) is used, it is possible that the predicted probabilities may be either negative or greater than one. Logically, a probability must fall between zero and one. The probit model uses a cumulative normal function that essentially smoothes out the regression line so that all of the predicted probabilities fall between zero and one.

variables that can be matched are used. Although Grossman and Joyce (1990) estimate a similar equation in their model, this initial stage is not of any great significance. The results show that none of the significance levels are changed when the inverse Mills ratio (the correction statistic) is not included.

Wanted reflects whether the woman wanted the pregnancy when she became pregnant. The question specifically asks the woman about her attitude toward pregnancy *before* becoming pregnant: therefore, this is a predetermined variable. Warner (1998) included this variable in his model in order to control for sample selection rather than estimating an equation similar to this one. A priori, one would expect that if a woman wanted to become pregnant then she is more likely to continue her pregnancy to full term, barring any unforeseen circumstances such as a spontaneous miscarriage.

Stage two of the treatment effects model

Recall back to the theoretical model that a woman chooses the type of insurance coverage that maximizes her utility. This can be shown by comparing her indirect utility functions (derived in the theoretical section):

$$27.\ V^{NO}(D^{LT}, Z^{H}, Z^{D}, P^{NO}, I) \quad v. \quad V^{MC}(D^{LT}, Z^{H}, Z^{D}, P^{MC}, I, MCP, \phi)$$

$$28.\ V^{NO}(D^{LT}, Z^{H}, Z^{D}, P^{NO}, I) \quad v. \quad V^{PI}(D^{LT}, Z^{H}, Z^{D}, P^{PI}, I, prem, \gamma, PI)$$

$$29.\ V^{MC}(D^{LT}, Z^{H}, Z^{D}, P^{MC}, I, \phi, MCP) \quad v. \quad V^{PI}(D^{LT}, Z^{H}, Z^{D}, P^{PI}, I, prem, \gamma, PI)$$

These equations illustrate that insurance choice is a function of all of the exogenous variables in the system. In addition, since insurance coverage is a choice, the decision to participate in Medicaid, purchase private insurance, or be uninsured is endogenous in the model. I suggested earlier that a treatment effects model is the superior model to use in

order to evaluate the effect of insurance coverage on prenatal care and birth weight, while controlling for sample selection and endogeneity.

Two univariate probits are estimated on the probability of having insurance and the probability of participating in Medicaid. From these two probits, two inverse Mills ratios can be computed. Both the inverse Mills ratios (to correct for sample selection) and the actual binary variables (to capture the direct effect of that variable) are included in the prenatal care and birth weight equations.

The decision to estimate two univariate probit models rather than some alternative specification is due to the following reasoning. The decision to participate in Medicaid and private insurance can be estimated as two univariate probits, a multinomial logit, or jointly as a bivariate probit. Note that one category, in this case no insurance, must always be excluded. A multinomial logit allows for more than one choice category. According to Kennedy (1993), a multinomial logit is characterized by the independence of irrelevant alternatives. This means that each of the choices must be mutually exclusive and that what affects one will not affect the other. As well, if more choices are added or if any of the choices are taken away, the probability of choosing a particular option remains constant. While this seems like a reasonable model for estimating the presence of insurance, the data used in the estimation process do not satisfy the independence of irrelevant alternatives requirement, or the mutual exclusiveness requirement.

An alternative to the multinomial logit is the bivariate probit. A bivariate probit takes into account the mutual inclusiveness of choices similar to a seemingly unrelated regression (SUR) model. In this model, this presumes that a significant percentage of women choose to have both Medicaid and private insurance. This is not the case in the

data set (NMIHS) nor is it theoretically logical to have two types of insurance at the same time. Therefore, this alternative is not chosen. Cutler and Gruber (1996) provide additional evidence that univariate probits should be estimated in this situation.

Two reduced-form[47] univariate probits are estimated on the probability that a woman participates in Medicaid or purchases private insurance. While these equations are of interest themselves, they also generate the correction statistics that appear in the prenatal care and birth weight equations to control for endogeneity:

2. $$\textit{Medicaid} = \gamma_1 + \gamma_2 \textit{ability} + \gamma_3 \textit{environmental} + \gamma_4 \textit{anthropometric} + \gamma_5 \textit{maternal} + \gamma_6 \textit{fertility} + \gamma_7 \textit{demographic} + \gamma_8 \textit{income} + \gamma_9 \textit{cohab} + \gamma_{10} CESD^{avg} + \gamma_{11} \lambda^{LIVE} + \varepsilon^{MC}$$

3. $$\textit{Insurance} = \alpha_1 + \alpha_2 \textit{ability} + \alpha_3 \textit{environmental} + \alpha_4 \textit{anthropometric} + \alpha_5 \textit{maternal} + \alpha_6 \textit{fertility} + \alpha_7 \textit{demographic} + \alpha_8 \textit{income} + \alpha_9 \textit{cohab} + \alpha_{10} CESD^{avg} + \alpha_{11} \lambda^{LIVE} + \varepsilon^{PI}$$

Ability is defined by the mother's and father's industry and occupation, the state Medicaid income ***eligibility*** level (in dollars), and the state ***unemployment*** rate. The industry and occupation in which the mother and father are employed reveal how easily it is to obtain private insurance and also may indicate the costliness of the insurance premium. The excluded category for industry is if either the mother or father (or both) are unemployed or if the father is not present. ***Unemployment*** is a good indicator of the job availability as well as of the job market environment in general. If someone in the household is gainfully employed, the probability of having private insurance is higher. Conversely, if no one in the household is employed, the probability of participating in Medicaid is higher.

[47] These are pure reduced-form equations where only exogenous variables are included on the right-hand side.

Medicaid ***eligibility*** is an important variable in the model. There are two ways that this variable can be included. The first way is to actually impute a woman's eligibility. If she is technically eligible, then eligibility is "turned on" and if she is not eligible it is "turned off". The problem with this measure is that it is endogenous and also may suffer from measurement error. Theoretically, a woman could reduce her income to the point that she becomes Medicaid eligible. If this measure is used, its endogeneity must be controlled for (not always an easy task). Cutler and Gruber (1996) suggest using an exogenous measure of eligibility. Using a complicated algorithm, their measure weights the income eligibility threshold (in dollars) by household size. I use the 1988 federal poverty level incomes (**Appendix 2**) and the 1988 Medicaid eligibility guidelines (**Table 24**) to create a similar measure of eligibility that is also exogenous. This measure, a function of each woman's household size and state of residence, is derived in **Appendix 3**[48]. It is expected that the higher the eligibility level (i.e. income of $20,000 is more generous than $10,000 since it allows a family to earn more and still be eligible) the greater the probability a woman participates in Medicaid. All other variables are explained in the next section.

Final stage of the structural-form treatment effects model

There is an important reason why depression is not entered endogenously, and is estimated as a separate equation in the empirical model. The original intent behind incorporating depression into the framework was to estimate its impact on insurance choice, prenatal care and infant health. It is assumed that a depressed mom may select into a sub-optimal type of insurance or demand a sub-optimal amount of prenatal care,

[48] This is just a rough approximation of a woman's eligibility. Actual Medicaid eligibility is computed

and that her depressed state may affect the health of her infant. However, it was realized that depression may not only be an exogenous input into the production process but it may also be an output. Post-partum depression is the most common example of this output. Among other things, post-partum depression is a direct result of giving birth to a child. In this context, depression is endogenous and must be estimated as a separate equation. Conceptually, this equation would explain the causes of post-partum or other types of transitory depression. Knowledge of these causes may be extremely useful in detecting depression and in prescribing a course of treatment for depression. But, the original intent of this dissertation was to understand the causes of infant health, not necessarily maternal health. While the framework proposed may provide some insight into understanding the causes of post-partum depression, this issue is not dealt with here. However, it would be an interesting extension of this dissertation for future research.

I develop a more accurate empirical measure of long-term (exogenous) depression to include in the model. Recall that the CES-D scale is measured for each woman an average of 17 months following childbirth. Using this measure alone as a predictor of maternal behavior *before* delivery is somewhat of a stretch. Since only one discrete measure of the scale is taken in the 1988 survey, it likely reflects a combination of long-term and transitory (such as post-partum) depression. However, the 1991 follow-up of the NMIHS takes a second measure of the CES-D scale for each woman. Averaging the two measures (from the 1988 and 1991 surveys) should provide a more accurate picture of a woman's long-term mental health. For example, if the 1988 measure is truly a measure of post-partum depression then the effects of this should be partially canceled

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using a very complicated algorithm that constantly changes over time.

out by her "true" state of mental health measured in the 1991 survey. I assume that the averaged CES-D ($\boldsymbol{CES\text{-}D^{avg}}$) is exogenous[49] since it more likely reflects long-term depression. Consequently, it is included as an explanatory variable in the prenatal care, birth weight, and insurance equations.

The model in the final stage is estimated by two-stage least-squares (2SLS). It is a recursive model since prenatal care is one input that enters into the infant health production function (birth weight), but birth weight does not enter into prenatal care demand. Recall from the theoretical model[50] that prenatal care is a function of long-term depression ($\boldsymbol{D^{LT}}$), factors that affect infant health ($\boldsymbol{Z^{H}}$), factors that affect transitory depression ($\boldsymbol{Z^{D}}$), prices ($\boldsymbol{P^{NO}}$, $\boldsymbol{P^{MC}}$, $\boldsymbol{P^{PI}}$), income ($\boldsymbol{I}$), Medicaid participation and the welfare stigma ($\boldsymbol{MCP}$ and ϕ) if a woman participates in Medicaid), and private insurance participation ($\boldsymbol{PI}$), its associated quality effect (γ), and the private insurance premium ($\boldsymbol{prem}$) if a woman purchases private health insurance. Empirically, the semi-reduced-form[51], prenatal care equation is given by the following:

$$\textbf{4. } \boldsymbol{Prenatal\ care} = \delta_1 + \delta_2 \boldsymbol{environmental} + \delta_3 \boldsymbol{anthropometric} + \delta_4 \boldsymbol{maternal} + \delta_5 \boldsymbol{fertility} + \delta_6 \boldsymbol{demographics} + \delta_7 \boldsymbol{income} + \delta_8 \boldsymbol{cohab} + \delta_9 \boldsymbol{CESD^{avg}} + \delta_{10} \boldsymbol{Medicaid} + \delta_{11} \boldsymbol{insurance} + \delta_{12}\lambda^{MC} + \delta_{13}\lambda^{PI} + \delta_{14}\lambda^{LIVE} + \varepsilon^{PNC}$$

Prenatal care is defined as the onset of care *or*[52] the adjusted number of visits according to the ACOG guidelines.

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[49] Later I test for exogeneity and find that I cannot reject exogeneity.

[50] Refer to theoretical equations **7**, **15**, and **23**.

[51] A "true" reduced-form prenatal care equation includes ALL of the exogenous variables in the system. Since this is a recursive treatment effects model, I include the actual Medicaid and insurance dummy variables and their sample-selection correction statistics, making this equation only semi-reduced-form. In some sense, the prenatal care equation is structural although it does not include any endogenous variables.

[52] These measures are not used at the same time, although I did estimate the mode with both and found no significant results. Separate equations are run for the onset of care and the adjusted number of prenatal care visits.

The price of prenatal care is proxied by the inclusion of ***environmental*** variables including the state population density per square mile (***state population density***), a state health care price index (***H-index***), and whether the woman lives in an urban county (***urban***). I assume that as the price of a prenatal care visit increases, the number of visits obtained decrease, but I have no a priori assumption about how price affects the onset of care. A decrease in ***state population density*** (more rural) suggests that prenatal care may be sparser, increasing the delay in seeking care and reducing the number of visits. In terms of price, an increase in ***state population density*** (more urban) is associated with higher prices (urban areas are more expensive), reducing the number of visits but having an unknown affect on the onset of care. The ***H-index***[53] is a reasonable proxy of the price of a medical visit. It takes a weighted average of the prices of a hospital room, general medical and dental visit, and a bottle of aspirin. I assume that an increase in ***H-index*** reduces the frequency of visits. It is unclear what effect this has on the onset of care. Finally, ***urban*** is expected to be an even better measure of access to prenatal care since the variable is individual specific, not aggregate.

In order for the structural-form of the birth weight equation to be estimated, it must meet identifying restrictions so that the estimates obtained are meaningful. An identifying variable is an exogenous variable that is not correlated with one of the dependent variables. Since only two equations are estimated in the final stage, the prenatal care equation must include identifying variables that are correlated with prenatal care but not correlated with birth weight in order to identify the birth weight equation.

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[53] This index is comprised of a weighted average of the following: average cost per day for a semi-private hospital room (weight = .178); AMA's price of a general practitioner's routine exam on an established patient (weight = .356); ADA's price of an adult dental cleaning and periodic oral exam (weight = .356); the

Use of identifying variables ensures that the estimate of a structural parameter is an estimate of that parameter and not something else.

There is a variable in the NMIHS that identifies a variety of barriers that a woman is said to face in getting prenatal care. Specifically, the types of barriers identified are: financial barriers[54], time barriers[55], and emotional barriers[56]. Several studies[57] have identified barriers in getting prenatal care including financial barriers, language barrier, difficulty in scheduling prenatal appointments, unaware of the importance of prenatal care, lack of transportation, ambivalence about the pregnancy, stress, unaware of where to receive prenatal care, expectation of no pregnancy complications (Higgins & Burton, 1996; Harvey & Faber, 1993;). While this is an ideal variable to include in the prenatal care equation in order to identify birth weight, surprisingly very few women in the NMIHS sample reported facing any barriers at all[58]. Therefore, this variable cannot be used at all since it has little variation. The environmental variables described above as well as household ***income*** and cohabitation with the father (***cohab***) are used as

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price of a 100 tablet bottle of Bayer aspirin (weight = .11).

[54] This variable reflects any one of the following problems: insurance did not cover prenatal care; could not pay for prenatal care; problem with Medicaid; required cash deposit; no insurance; provider would not accept Medicaid; unspecified money/insurance problem; unclassifiable money/insurance problem.

[55] This variable reflects any of the following problems: no transportation: no child care: could not miss work/school; no doctor/clinic near; did not know where to go; could not get appointment; had to wait too long; hours not convenient; unspecified appointment/work/transportation problem; unclassifiable appointment/work/transportation problem.

[56] This variable reflects any of the following problems: afraid of tests; did not like MD/nurse attitude; did not know pregnant; did not want anyone else to know; had too many other problems; did not want to be pregnant; unspecified provider problem; unclassifiable provider problem; unspecified other problem; unclassifiable other problem.

[57] Harvey, S.M. and K.S. Faber, "Obstacles to Prenatal Care Following Implementation of a Community-Based Program to Reduce Financial Incentives", *Family Planning Perspectives*, 25(1): 32-37, 1993. Barriers to prenatal care were studied in a group of women in rural Oregon bettween 1988 and 1990. Despite the establishment of a program to provide prenatal care to low-income women, the reasons most frequently cited as barriers were difficulty in paying for prenatal care (70%), difficulty with medical insurance (55%), ambivalence or fear about the pregnancy (46%) and transportation problems (42%).

[58] There were less than 20 women in the entire sample who reported having barriers to prenatal care.

instruments and are included in the prenatal care equation but not in the birth weight equation.

Medicaid participation is given by ***Medicaid*** (and λ^{MC}) while private insurance participation is defined as ***Insurance*** (and λ^{PI}). Theory suggests that Medicaid participants obtain more prenatal visits than uninsured women but makes no a priori assumptions about its effect on the onset of prenatal care. Likewise, theory suggests that women with private insurance receive more prenatal visits but suggests nothing about the onset. Household ***income*** is expected to impact prenatal care in a favorable manner. It is expected that as income increases, more prenatal visits are demanded, but it is unclear what the effect is on onset.

Long-term depression (D^{LT}) is defined as the $CES\text{-}D^{avg}$ scale. This is an average of the CES-D scores from the 1988 NMIHS and the 1991 NMIHS. Several studies (including Wells et al., 1989; Hays et al., 1995) indicate that depressed individuals function physically and emotionally poorer and miss more days of work and school than non-depressed individuals. Therefore, I assume that depressed women obtain later and less frequent prenatal care.

In the theoretical model, the production of infant health is a function of prenatal care, M, long-term depression, D^{LT}, and factors that affect infant health, Z^{H}. The structural birth weight equation is given by the following:

$$5.\ Birthweight = \beta_1 + \beta_2 anthropometric + \beta_3 maternal + \beta_4 fertility + \beta_5 demographics + \beta_6 CESD^{avg} + \beta_7 Medicaid + \beta_8 insurance + \beta_9 prenatal\ care + \beta_{10}\lambda^{MC} + \beta_{11}\lambda^{PI} + \beta_{12}\lambda^{LIVE} + \varepsilon^{BWT}$$

Factors that affect infant health (Z^H) are defined as several different categories of variables. ***Anthropometric*** characteristics include the ***mom's height***, ***mom's birth weight***, and whether the child is ***male***. As suggested by Warner (1995, 1998) anthropometric characteristics that control for the mother's physical structure are included since they are good predictors of birth weight. ***Male*** is also included in a similar spirit since boys are typically born heavier than girls are.

Maternal behaviors are defined as ***smoking*** and ***drinking*** during the pregnancy. Fertility behaviors include ***parity*** (indicating whether the woman had any previous pregnancies), ***age***, the ***wanted***ness of the pregnancy, the prior number of ***fetal deaths*** experienced by the mother, and the number of the mother's own children (living with her), ***kidcohab***. Rosenzweig and Schultz (1982, 1983) introduced the concept that parental behavior affects the choice of inputs that enter into the infant health production function. One of these behaviors is smoking. Numerous studies have shown that maternal ***smoking*** during pregnancy reduces birth weight and increases gestation. Some may argue that smoking is a choice or endogenous variable (Rosenzweig and Schultz, 1982, 1983). However, in light of the fall of the tobacco industry in the past few years, it has been proven that smoking is addictive. Becker (1988) formalizes the concept of addictive behavior in his model of rational addiction and explains the difficulty in curtailing addictive behavior. If a woman wants to become pregnant and recognizes the harmful effects of smoking, she is likely to devote time and resources toward quitting before conception. If a woman becomes unexpectedly pregnant, she is less likely to continue the pregnancy. This effect is controlled for by the initial stage of estimation. Unless a woman began smoking *during* her pregnancy, her smoking behavior is

predetermined and thus exogenous. Several studies include smoking as an exogenous variable (Warner, 1995, 1998). Since prenatal care, Medicaid, and private insurance are challenging to identify, smoking is left exogenous.

The ***fertility*** variables are included since they are also expected to impact a woman's behavior concerning the pregnancy. ***Parity***, an indicator of whether the woman had any previous pregnancies, reflects the mother's fertility. Rosenzweig and Schultz (1982, 1983) find that parity has a significant effect on both birth weight and (decreasing) gestation. ***Fetal deaths*** and ***kidcohab*** are expected to explain a woman's previous fertility behaviors and should help to explain birth outcomes. ***Age*** is also argued to reflect fertility behavior since a woman's fertility varies with her age. Rosenzweig and Schultz find that the mother's age at childbirth significantly affects birth weight in a non-linear way. For this reason, age^2 and age^3 are included to capture the non-linearity. Finally, ***wanted*** is assumed to impact a woman's fertility behavior as well.

Demographic variables including ***education*** and whether the woman was ***never married*** are included to control for individual effects. Recall that the entire analysis (Stage Two and the Final Stage) is stratified by race yielding distinct white and black samples. Therefore, race cannot be included as a regressor. ***Education*** is defined as the number of years of education. I assume that women with more years of education are better able to understand the importance of adequate prenatal care and demand more frequent and earlier care. In addition, I assume that higher educational attainment is expected to increase birth weight since women with more knowledge are likely to better understand the necessity of healthy behaviors. Since Rosenzweig and Schultz (1982, 1983) find that education enters into the birth weight production function non-linearly, I

include edu^2 and edu^3 as well. Marital status is defined by whether the woman has never been married. I expect that not having ever been married reflects less responsible behavior on the mother's part and is associated with later and less frequent prenatal care and worse health outcomes.

Depression (long-term) is measured by the $CES\text{-}D^{avg}$ scale. I expect that long-term depression or $CES\text{-}D^{avg}$ reduces birth weight. Several studies discussed earlier indicate that depressed mothers pass on their depressed condition to their infants in the form of reduced left frontal brain activity. The expectation here is that depressed mothers bear unhealthy infants. Timely and more frequent prenatal care is expected to increase birth weight.

Recall that the treatment effects model allows for the actual ***Medicaid*** and ***Insurance*** variables to be included. Consistent with the theoretical model discussion, I expect that Medicaid participants bear lower birth weight infants while women that participate in private insurance bear heavier infants. Finally, the three inverse Mills ratios: λ^{MC}, λ^{PI}, and λ^{LIVE} are included to control for sample selection. Along the lines of previous discussions, I expect that λ^{MC} reduces birth weight while λ^{PI} and λ^{LIVE} increase birth weight.

Results[59]

Private Insurance and Medicaid

[59] All standard errors have been corrected for general heteroskedasticity with the assistance of Bill Greene and Limdep. Recall again that since it is likely that several forms of heteroskedasticity exist it is most appropriate to adjust the standard errors using a method similar to White (1980).

Results from the private insurance and Medicaid equations can be found in **Table 15**. The private insurance and Medicaid univariate probits are both stratified by race and by all births and term births. Only the full sample is reported here since the term births yield similar results. In all but the white private insurance equation, eligibility is significant and of the right sign. The inclusion of Medicaid dollar eligibility is to gauge whether a woman is likely to be eligible to receive Medicaid or to gauge how easily it is to get Medicaid. In both the black and white Medicaid equations, the higher the dollar eligibility threshold, the more likely a woman participates in Medicaid. This provides some initial evidence that an effective policy tool at increasing insurance coverage is to increase the dollar eligibility threshold. On the other hand, both the white and black private insurance equations reveal some evidence of crowding out, although this is only statistically significant in the black equation. As the dollar eligibility threshold increases, there is a decrease in private insurance participation. A much more detailed discussion of the relationship between eligibility and Medicaid appears in **Chapter IV**.

The results on the unemployment rate are interesting. The unemployment rate can be a reasonable gauge at how easily it is to obtain private insurance through one's job. A negative and significant coefficient in the white private insurance equation suggests that it is more difficult to obtain employment with benefits as the state's unemployment rises. However, a negative and significant coefficient in the black Medicaid equation suggests something different. Perhaps this reflects a state's ability to provide Medicaid. One possible story is that as a state's unemployment rate rises, the economic conditions worsen, and the state cannot afford to provide good access to Medicaid. Maybe they can

offer Medicaid, but perhaps cannot offer the adequate outreach programs or maintain the necessary welfare staff to get people enrolled.

While the industry and occupation results are not reported in **Table 15**, there are a handful of significant results. In large part, the coefficients in the Medicaid equations are negative and as expected, insignificant. One would assume that the majority of people who participate in Medicaid are not gainfully employed. Therefore, the generosity of an industry's or occupation's benefits package would not affect those not in the industry or occupation. On the other hand, many of the coefficients in the private insurance equations are positive, and several are significant, but more so in the black equation and for the woman's own industry. Industries typically associated with strong labor unions, the construction and manufacturing industries, have significant and positive coefficients in the black equations. This suggests that unions are able to help provide private insurance. However, the coefficient on construction in the white equation is negative and significant. These results may suggest some discrimination again whites in the construction industry or that unions fight harder for black workers. Or simply this could mean that blacks and white have different jobs within the industry. These same results appear in the retail industry as well.

Depression is significant in all equations but the white, private insurance. This suggests the importance of including depression in this type of a framework. In both Medicaid equations, the coefficient is positive. Depressed women are more likely than other women to participate in Medicaid. One explanation is that depressed women are in greater need of medical care and may be receiving treatment for depression. On the other hand, the coefficient in the black, private insurance equation is negative. But this result is

not without explanation. Literature suggests that depressed individuals have difficulty performing every day tasks and miss more days of work than non-depressed individuals. Therefore, it is rational to argue that depressed women are less able to maintain gainful employment, and thus, are less likely to obtain private insurance.

The state health care price index measures the costliness of health care in the state. This coefficient is negative and significant in the white, private insurance equation. This may suggest that employers are either less likely to offer insurance or offer insurance at higher premiums in states where the cost of health care is higher. Reducing the cost of care in a state may provide greater access to private insurance. In addition, women who live in more urban states are also more likely to have private insurance, but less likely to participate in Medicaid. Generally, urban areas provide more opportunities for gainful employment since businesses tend to migrate toward urban areas. This result illustrates a type of reverse crowding out where urbanization encourages greater participation in private insurance and less participation in Medicaid.

One might expect that women who plan and want a pregnancy are more likely to wait until they are privately insured to become pregnant. The wantedness of the pregnancy is significant, but only in the white equations. Women who wanted the pregnancy are more likely to be privately insured and less likely to have Medicaid. It is possible that participation in Medicaid is an afterthought or a result of getting pregnant, rather than a result of wanting to become pregnant. The coefficient on women with their own children living in the household is significant in every equation but in the white, Medicaid equation. In both private insurance equations, the coefficients are negative. These results are validated in the black equations. This may suggest that the more

children a woman has, the more expensive private insurance becomes or the less likely it is affordable, particularly for large families. This result is somewhat counterintuitive since one might expect economies-of-scale in health insurance. For this reason, having more children should increase the likelihood of having private insurance.

There are several other variables that are significant in the Medicaid and private insurance equations. Both the cohabitation with father and income variables are significant in all equations, positive in the private insurance equations and negative in the Medicaid. These results are expected. Cohabitation suggests greater ability and access to insurance. A single mother may have less access, and therefore participate in Medicaid. Higher incomes are also associated with greater participation in private insurance and less in Medicaid. Smoking reflects adverse selection in Medicaid but positive selection in private insurance. That is, smoking is significant and negative in the private insurance equations but significant and positive in the Medicaid equations. This suggests that women with healthier lifestyles (who do not smoke) select into private insurance while women with poor health habits select into Medicaid. These results, while mostly not significant, are also shown with drinking. Finally, all three specifications of age are significant in most of the equations. The sign pattern indicates a significant non-linear effect such that getting older increases the probability of participating in Medicaid and decreases the probability of having private insurance. Over time, this effect reverses for middle-aged women (in the sample which may be in the thirties) then returns to the initial pattern for oldest women (in their forties).

Prenatal care

There are four prenatal care equations estimated in the TEM where prenatal care is defined by the onset of care and the ACOG adjusted number of visits. Each equation is stratified by race. The equations are not very robust across the different specifications and the most action occurs for white women in the ACOG adjusted visits equation. However results from the term birth equations are similar to their full sample counterparts. Results for all births appear in **Table 16**.

Discussion from the theoretical model suggests that a woman with private insurance receives the most adequate and timely prenatal care since having insurance permits easier access to care. In the empirical model, the excluded category (or base case) is self-paying or having no insurance. Therefore, a positive coefficient (on private insurance or Medicaid) suggests better access to care (or perhaps a positive quality effect) than self-paying and a negative coefficient suggests poorer access to care (or negative quality) than the self-pay case. In all but the black, ACOG equation, the coefficient on private insurance is significant and positive in visits and significant and negative in onset[60]. Having private insurance decreases the onset of care and increases the number of adjusted visits. Recall that these are both favorable results since earlier onset and more visits are desired. Furthermore, this indicates that private insurance provides better access to care than having no insurance (the base case). Participating in Medicaid also suggests better access although the results are only significant in the white, visits equation[61]. Overall, these results may suggest that both private insurance and Medicaid provide higher quality care than self-payment. However, it is unclear whether *earlier* and

[60] Recall though that a negative coefficient in the onset equation is a favorable result since earlier onset is better.

more frequent care reflects higher *quality* care. They may just reflect better access to care. The results from the birth weight equations should provide better evidence of quality effects since higher birth weights do tend to reflect higher quality. Nonetheless, having some form of health insurance seems to provide better access to care than having no insurance at all.

I assume that the variables that affect access and availability to prenatal care should matter most. Both the number of own children in the household and the number of drinks consumed during pregnancy decrease the number of visits. The latter, however, is only significant for whites. Having children in the household can be a constraint on time, energy and resources. Additionally, drinking may affect one's ability to act rationally. Both of these variables act as barriers to prenatal care and should be expected to reduce the number of visits obtained and delay the onset of care. On the other hand, few of the variables that reflect the state climate (state population density, urban, and the state health care price index) are significant. Two of these three variables are state level or aggregate variables and may not be good indicators of access to care since they are not specific to the woman. However, for white women, the more urban the county of residence or the more densely populated the state, the earlier she started care. This result is expected since the proximity to a prenatal care provider is closer and there is a greater availability of transportation. Finally, cohabitation with the father of the child is negative and significant in the black, onset equation. Living with the father allows a woman to seek prenatal care earlier and also increases the ability to get to a prenatal visit by his assistance with transportation and child care.

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[61] It is possible that women who participate in Medicaid substitute quantity for quality by demanding more

It was explained earlier that the wantedness of the pregnancy might be a good predictor of sample selection. However, since the live birth selection statistic is included in the model along with wantedness, the wantedness measure may be capturing less of the sample selection and more of the true wantedness of the pregnancy. Results indicate that the more the woman wanted the pregnancy, the earlier she sought prenatal care. Generally, women of childbearing age are equipped with information from their providers and even the media that the early onset of prenatal care is important (although my results do not support this argument). Therefore, it is rational to assume that women who want a pregnancy are likely to receive care earlier than those who do not want the pregnancy. In addition, results indicate that the more prior fetal deaths the woman had, the more visits she makes. If a woman has a poor pregnancy history, she is likely to be concerned about this pregnancy. One means of addressing this concern is to seek frequent prenatal care.

The mother's age is included as a squared and a cubed term in order to detect any non-linearity in prenatal care use according to age. The results indicate that all three age variables are significant in the white, ACOG adjusted visits equation and are almost significant in the onset equation (but of the reverse sign). As one might expect, the sign pattern switches from plus to minus back to plus. This indicates that prenatal care use increases at younger ages, then decreases or at least flattens at an intermediate age, then increases once again as the woman ages even further. This is consistent with previous literature that concludes young women and older women use more prenatal care that the average age mother. Younger women are more uncertain about the pregnancy since they are still maturing themselves, and older mothers are at higher risk. By evaluating the

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frequent, lower quality visits.

derivative of the cubic (i.e. age + age^2 + age^3) equal to zero, one can evaluate the slope of the function and determine the specific ages that the slope equals zero. Prenatal care use increases from age 15 to age 25, then decreases after age 25 until age 34, than finally increases again after age 34 until age 45 (the maximum age in the sample).

Results from the live birth correction statistic indicate that no significant selection effect exists. Finally, the results on the depression variable are of some interest although most of the coefficients are not statistically significant[62]. In all four equations in the full sample model the coefficient on depression is positive. This suggests that depressed women receive later prenatal care but more visits, although this is significant only in the white, visits equation. These results begin to suggest that policies should be targeted at reducing depressive symptoms in pregnant women. Later results found in the birth weight equations and in the policy simulations further support such a policy.

Birthweight

Results from the birth weight equations are moderately robust across the different specifications of birth weight (i.e., birth weight and term birth weight), with a few important differences between black and white births. The treatment effects model is estimated eight times, with birth weight (in grams) and term birth weight (where the sample is limited to gestations of at least 37 weeks) as the dependent variables, prenatal care measured in weeks of onset and by the ACOG adjusted number of visits, and each of these equations are stratified by race. Results from both the full sample and term birth weight sample models can be found in **Tables 17** and **18**

[62] Insignificant results here suggest that one avenue for depression to affect birth weight is shut down.

The coefficients on a woman's anthropometric characteristics (mother's own birth weight, mother's height, and child's sex) are positive and significant in every birth weight equation. Warner's (1995,1998) argument for including these characteristics is right on the mark. I argue that these strong results suggest two things. The first is that there is an intergenerational transfer of anthropometry from mother to child that is consistent with medical research that says genetics play a large role in determining one's health. However, the second is that *if* genetics do play a large role in determining birth weight, there is less for the economist to say. While the economist is equipped with the proper tools to explain how income and insurance play a role, the economist is not well equipped in understanding the bio mechanics that explain how anthropometric characteristics are passed on. But, these findings are important in that they may signal medical researchers to continue genetics research. Additionally, the importance of improving current infant health (or birth weight) is heightened in light of the intergenerational transfer.

A related characteristic to anthropometry is the number of prior fetal deaths that the women had. Unfortunately, the data do not indicate whether the death was voluntary (i.e. abortion) or involuntary (i.e. miscarriage). It is therefore assumed that these deaths are a mixture of the two. In both the white and black birth weight equations with onset as the measure of prenatal care and in the black birth weight equation with the ACOG adjusted visits as prenatal care measure) the coefficient on the number of fetal deaths is negative and significant. If the fetal deaths were miscarriages, then these results indicate an underlying health problem. That is, if a woman had a previous miscarriage, and her child in this sample is born at a lower birth weight, then it is reasonable to conclude that the woman must face some underlying health problem. She reveals a history of poorer

birth outcomes. On the other hand, if the fetal deaths were abortions, then this becomes a selectivity issue. If this woman previously aborted her fetus, then on some level, she may value the pregnancy less and may be less likely to properly care for herself during the pregnancy. The result is a lower birth weight infant. However, wantedness is controlled for here. The only wrinkle to this story is that the coefficient on fetal deaths is positive and significant in the white, term birth weight equation (with onset as the prenatal care measure). An alternative story may be that a woman who experienced a prior fetal death is so aware of the adverse outcomes associated with pregnancy, that she takes extremely good care of herself during the pregnancy which results in a higher birth weight infant. If this is true, then this provides some evidence that maternal behavior may affect infant health.

One of the main contributions of this dissertation is to evaluate the impact of maternal depression on birth weight. While studies (Field, 1998; Jones et al., 1997; Dawson et al., 1997a; Dawson et al., 1997b; Locke et al., 1997) have shown that depressed mothers can pass their depressed state to their infants in the form of reduced brain activity, no study has evaluated its impact on birth weight. In all of the black equations the greater the depression scale measure, the lower the birth weight. While depression is not significant in the white equations, it is negative throughout. One explanation for significant results in the black equations (but not in the white equations) is that there is a much higher prevalence of depression in black women. This is evident in the key variable means discussed earlier. A higher prevalence of depression may increase the significance of the standard errors although it should have no effect on the

sign or magnitude of the coefficients. The policy implications are women of childbearing age should be targeted for a mental health assessment at their prenatal care visits.

The coefficient on parity is positive and significant in black and white term birth weight with onset and black term birth weight with ACOG adjusted visits equations. This seems to indicate that having had a previous pregnancy increases the birth weight of future born children. This is not to say that a first born child is not healthy, but is appears as though subsequent children are even more healthy.

Consistent across every birth weight equation is that neither specification of prenatal care is significant. These results are disappointing but not surprising, and may be due to several different factors. The first is a lack of poor instruments. The second is that many of factors aside from medical care influence one's health. This hypothesis is argued in the Field model of health determinants (Blum, 1981). Blum's paper illustrates force-field and well-being paradigms of health where heredity, the environment, life styles, and medical care all influence one's health and well being. Therefore, medical care is only one piece of the puzzle and may not significantly impact health alone. A third reason some argue (for example, Mahan, 1996) is that the type of services provided at a prenatal care visit that matter rather than the visit itself. The data used in this analysis may not be rich enough to unravel the specific type of services offered. Nonetheless, evaluating what is offered at a prenatal care visit rather than quantifying prenatal care proves to be a valuable path of future research. A natural link to this is to further evaluate enhanced prenatal services, particularly ones provided by Medicaid.

The number of cigarettes smoked during the pregnancy is negative and significant in all birth weight equations. This is consistent with prior research and

illustrates that maternal behavior can affect infant health. Not only does smoking reduce birth weight, but it also slows fetal growth. The rationale for this conclusion is the following. The difference between birth weight and term birth weight is that gestation is controlled for. If babies are born at a lower birth weight because they are born at a shorter gestation, then it cannot be deduced that the fetus is growing slower than normal. However, if a baby is born at a lower birth weight but is of normal gestation, then it must be the case that the rate of fetal growth is slower than normal. Therefore, one can conclude that smoking may not necessarily reduce gestation but rather may slow down fetal growth. A weaker result can be found with drinking. The coefficient on drinking is negative and significant in only the black, term birth equations.

One of the hypotheses suggested in the theoretical model is that the quality of care provided under Medicaid is inferior to that of private insurance and the self-payment provides the lowest quality of care (due to bad debt). One way to address quality effects is to evaluate the effect of Medicaid and private insurance on birth weight[63]. Recall that self-payment is the excluded category or base case. This means that a positive coefficient on Medicaid or private insurance suggests lower quality care than self-payment while a positive coefficient indicates higher quality care. In the white birth weight equation with onset and in both of the black, term birth weight equations, the coefficient on Medicaid is negative and significant (but also negative in the white, ACOG equation). This indicates that the quality of care under Medicaid is inferior to the self-pay case, ceteris paribus. Since any selectivity bias due to participation in Medicaid is controlled for by employing the treatment effects model, these results should be signaling quality rather than selection.

However, it is possible that this result is also picking up income since income does not appear in the birth weight equation. The policy implications of this result are important and the policy simulations can shed more light on this. None of the coefficients on private insurance are significant. This suggests that the quality of care under private insurance is equivalent to the self-pay case.

Finally, a discussion of the inverse Mills ratios is warranted. Though the three inverse Mills ratios used are included to control for sample selection, they are not typically significant. However, the Medicaid Mills ratio is significant (for black term births) suggesting a selection effect with Medicaid. However, it is their insignificance that has implications, particularly the live birth inverse Mills ratio. This is included to correct for the sample selection due to only evaluating women who experienced a live birth (versus all births including fetal deaths and abortions). This variable is not significant in any equation, although it is closer to being significant in some of the black equations. Grossman and Joyce (1990) find a similar pattern. I estimated all of these same models without the selection term, but none of the results changed significantly. This suggests that it is not necessary to control for this type of sample selection when including the wanted variable. This is precisely what Warner (1998) argued. While all of my results can be reported without the selection correction, I choose to report those that include it.

Alternative models

Five alternative models are estimated in order to test further hypotheses and to make additional comparisons. The first two models extend the treatment effects model

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[63] The policy simulation more thoroughly evaluates both the direct and indirect effects of Medicaid on

by a) addressing the exogeneity of depression and by b) including two insurance/onset interaction terms. The remaining three models are alternative models to the treatment effects model. These models include an instrumental variables model, a model that treats all previously defined endogenous variables as exogenous, and a pure reduced-form model. All five models use onset as the measure of prenatal care and birth weight as the measure of infant health. Additionally, separate models for blacks and whites are estimated.

The endogeneity of depression is also explored in the treatment effects model. A Hausman test fails to reject the hypothesis that depression is exogenous. The procedure to conduct this test is rather simple. Prenatal care and birth weight equations are estimated with both the actual value of $CESD^{avg}$ and a predicted value of $CESD^{avg}$. The predicted value is obtained from a separate OLS equation. Drug use variables are used as identifiers in the depression equation. The high insignificance of the predicted value of depression along with the significance of the actual variable is one means of determining that depression is not endogenous. However, a simple chi-squared statistic fails to reject exogeneity.

In order to further evaluate the effects of Medicaid, private insurance, and prenatal care in the treatment effect model interaction terms:

$$\textit{Medicaid} * \hat{\textit{Onset}} \quad \textit{and} \quad \textit{Private insurance} * \hat{\textit{Onset}}$$

are included as regressors in the birth weight equation. The first interaction term reflects the onset of care as a function of Medicaid participation while the second reflects onset as a function of private insurance. These interaction terms reflect the productivity of onset

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infant health

as a function of the type of insurance participation. For example, if Medicaid provides lower quality care than private insurance than the productivity of onset for women with Medicaid is less productive or has less of an impact, than the productivity of onset for women with private insurance coverage. Results indicate that none of the interaction terms are statistically significant but all are of the negative sign. This suggests that the effect of the early onset of care is similar regardless of the type of insurance coverage, although self-pay may be less productive.

This dissertation employs a treatment effects model (TEM) to evaluate the direct effect of private insurance and Medicaid on birth weight. The TEM is chosen over an alternative model since it allows for the direct effect of having insurance to be captured while controlling for the self-selection or endogeneity of insurance. However, some studies capture the effect of insurance or program participation with an instrumental variables (IV) model. In this case, an IV model estimates the predicted probability of having private insurance and Medicaid and include that as the regressor in the birth weight equation, rather than the variable itself. Inverse mills ratios are not included in the IV model. For comparison, I also estimate the birth weight equation using the IV approach. Results can be found in **Table 19**.

The results are fairly robust across the TEM and IV models, with a few major differences. The most important difference is that Medicaid is significant in the TEM but not significant in the IV model. It appears as though the IV approach does not capture the true effect of having Medicaid. It is only capable of capturing the effect of the predicted probability of having Medicaid rather than actually having Medicaid. This result alone gives some evidence that the TEM may be a superior means of estimating the effect of

insurance or participation in a public program on health outcomes. Alternatively, the ACOG number of adjusted visits is significant in one specification of the IV model, but is not significant in any specification of the TEM.

I also estimate the birth weight equations treating prenatal care, Medicaid, and private insurance exogenously. These results are found in **Table 20**. If the results change significantly across the two specifications (endogenous and exogenous models) then this may suggest simultaneity bias[64] and that it is necessary to endogenize these variables. Two examples (although there are more) of simultaneity bias are adverse and positive selection. If women who expect problem pregnancies begin care earlier then adverse selection exists. If women with healthy behaviors begin care earlier then positive selection exists. Results show that ACOG[65] is significant in the exogenous model, suggesting the existence of simultaneity bias. In this case, it is possible that simultaneity bias may over inflate the true effect of an endogenous variable. Medicaid is no longer significant in the black equations. This suggests that self-selection may be canceling out quality effects. Depression continues to be significant and is reasonably robust. Although the significance and sign patterns of many of the variables are robust across models, a few of the key variables (like prenatal care and Medicaid) are different. This suggests that it may be appropriate to include these variables are endogenous.

Finally, pure reduced-form birth weight equations are estimated for whites and blacks. The results of these can be found in **Table 21**. These equations are estimated in part to compare to the results found in Currie and Gruber (1996b). Currie and Gruber use aggregate data to evaluate the impact of Medicaid eligibility on the incidence of low birth

weight and infant mortality. They estimate reduced-form models where eligibility enters directly into the infant health equations. They find that an increase in Medicaid eligibility lowers the incidence of low birth weight. Results from my model indicate that eligibility does not have a statistically significant effect on birth weight for either blacks or whites. In support of my results, I argue that eligibility enters into the model in complex and non-linear ways and that is the reason that the treatment effects model is estimated. By entering eligibility directly into an infant health equation, one can only capture the linear effect of eligibility on birth weight. A further discussion of these results can be found in the next chapter.

Special study: Poor birth outcomes

There is currently a great deal of interest in understanding the correlates of low birth weight (less than 2500 grams/5.51 lbs.) infants as well as pre-term (less than 37 weeks gestation) deliveries. I estimate the treatment effects model twice more (actually eight times more stratifying by race and using both prenatal care measures) with low birth weight (a dummy variable indicating the incidence of low birth weight) and term low birth weight (a dummy variable indicating low birth weight in pregnancies where the gestation is greater than 37 weeks) as the dependent variables in the birth weight equation.

The results of low birth weight and term low birth weight can be found in **Tables 22** and **23**. Overall, the results do not differ significantly from the birth weight and term birth weight models. Surprisingly, neither specification of prenatal care is significant in

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[64] Simultaneity bias occurs when the variable is correlated with the error of the dependent variable.

any of the models. However, the coefficients (except one) are all of the expected sign. The earlier the onset and the greater the number of visits, the lower the probability of having a low birth weight infant. While one might suspect that prenatal care does not matter for healthy women, it was expected that it may matter for women with adverse health outcomes (i.e. low birth weight children). One explanation mentioned before is that the instruments included in the prenatal care equations are less than ideal. The lack of poor instruments may be driving the result. Another explanation may be that other factors such as a woman's anthropometric characteristics, prior pregnancy history, and behaviors such as smoking may explain most of the variation in birth weight.

Depression also does not have a significant impact on either low birth weight or on term low birth weight. However, in 7 of 8 equations, depression has a positive effect on the incidence of low birth weight. This means that the greater depression score increases the probability of low birth weight. The consistency of these results indicates that depression may have a systematic effect on infant health. These results, although insignificant, yield some evidence that the link between depression and infant health should be investigated further.

Another important result is that Medicaid participation seems to impart a low quality effect by increasing the incidence of low birth weight (for whites) and by reducing overall birth weights. These results are unlikely due to selection since the treatment effects model controls for selection. One possible explanation discussed earlier is that since Medicaid providers see such a large volume of patients they may more likely misdiagnose a pregnancy complication which may result in lower birth weight children.

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[65] This model is also estimated with ACOG as an alternative measure of prenatal care.

The purpose of evaluating the incidence of low birth weight is to determine not only the correlates of low birth weight, but to test whether those variables expected to impact infant health but are not significant in the birth weight specification, do significantly impact the incidence of low birth weight. The expectation is that there may be more that can be done for preventing low birth weight infants. However, the results show little difference between the correlates of birth weight, in general, and the incidence of low birth weight.

Conclusion

There are several interesting findings in the treatment effects model. One of the most important contributions of this dissertation is that depression is modeled into the production of infant health framework. This is the first study to recognize a woman's state of mental health in this context. Depression is found to significantly affect Medicaid and private insurance participation, the number of visits obtained during the pregnancy, but most importantly, birth weight. Results show that a higher depression score reduces birth weight, although this effect is not always significant. While other studies have shown that depressed mothers may pass on their depressed state in the form of reduced brain activity to their newborns, this is the first study to show some evidence that depression may also affect birth weight. In light of these findings, a depression simulation is conducted in the following chapter with the purpose of further exploring these findings. Evidence from the simulations supports these findings.

Depression has effects as early as the prenatal care and health insurance stage. Depressed women are more likely to have Medicaid and less likely to have private

Depression has effects as early as the prenatal care and health insurance stage. Depressed women are more likely to have Medicaid and less likely to have private insurance. These results suggest two things. The first is that depressed women may have a more difficult time securing private insurance through employment. If depressed women are treated for depression, then they may be more likely to secure employment with benefits. Alternatively, it may be the case that privately insured women receive better treatment for depression. Perhaps some of the women who responded as not being depressed had been depressed previously but had already been treated.

My results consistently show that prenatal care does not have a significant effect on infant health. This result is not entirely inconsistent with other results found in the literature, although some studies do find that prenatal care, in one form or another, has a significant effect on birth weight. However, the Field model of health determinants explains that medical care is only one factor in a set of several important factors that affect health. It may be that prenatal care along with health behaviors, a healthy environment, and good genetics all contribute to good health. My results indicate that smoking and to a lesser extent drinking are found to reduce birth weight and increase the incidence of low birth weight. This result, unlike the results from prenatal care, show that a woman's lifestyle and behaviors can affect infant health. Another important result is that almost across the board, a woman's anthropometric characteristics affect birth weight. Much can be determined about the birth weight of a child from a woman's own birth weight and her own height. This is a reasonable conclusion. These results all indicate that some aspects of infant health cannot be directly affected by policy (anthropometry

matters), while other aspects may be affected, but in a different matter than we may have thought.

CHAPTER IV

POLICY SIMULATIONS

Introduction

One of the most important policy issues of the past decade has been to develop an efficient policy tool that alleviates the number of uninsured people in the United States. Policymakers believe that greater access to health care coverage leads to more appropriate utilization of health care services and thus, more favorable health outcomes. In the context of this dissertation, this tenet suggests that greater access to prenatal care brings about increased demand for prenatal care and produces healthier infants. This tenet does not go without factual evidence. There is some weak evidence that indicates that adequate prenatal care does produce healthier infants (Rosenzweig & Schultz, 1982, 1983; Grossman & Joyce, 1990; Warner 1995, 1998). This contrasts to my finding that prenatal care has no impact on health outcomes. In addition, some studies have shown that one of the primary reasons that women demand less than adequate prenatal care is because they cannot afford it (Torres & Kenney, 1989). One way that Congress responded to this issue was by expanding the eligibility requirements for Medicaid. In the mid-1980's most states provided Medicaid only to the poorest pregnant women and children with incomes far below the federal poverty level (FPL). Today, the federal Medicaid income eligibility floor is set at 185% of the FPL with some states extending eligibility as high as 400% of the FPL.

Despite studies like Torres and Kenney (1989), expanding eligibility requirements alone may not ensure better health outcomes if newly eligible women do not actually participate. While states are allocating additional resources toward Medicaid outreach programs and toward simplifying programmatic enrollment, not all women that are eligible participate[66]. On the other hand, some individuals shift away from their private insurance coverage into Medicaid upon becoming eligible. The policy simulation finds some evidence of this.

This dissertation seeks to evaluate the impact of expanding Medicaid income eligibility requirements on prenatal care demand and birth weight. Using the recursive treatment effects model of prenatal care onset and birth weight, I conduct a policy simulation that evaluates the impact of expanding Medicaid from the 1988 income eligibility levels to the 1997 levels. This policy simulation is an improvement over other studies in the literature since it takes into account all of the different channels that a change in eligibility may have on birth weight. A change in eligibility may affect the probability of having Medicaid or private insurance. The change in these probabilities may then directly affect birth weight and may indirectly effect birth weight through its effect on prenatal care. The simulation captures all of these channels. In addition, another favorable aspect of this method is that Medicaid participation is not forced upon an individual. I estimate the predicted probability that a woman participates in Medicaid and private insurance rather than haphazardly assigning some women to Medicaid and others to private insurance. Evidence has shown that not all women who are Medicaid eligible participate. Keeping this in mind, I also estimate Medicaid take-up rates (the rate at

[66] See **Table 3.**

which eligible women participate) of the women in the NMIHS sample, stratifying the analysis by race. Finally, simulating the effects of a change in eligibility allows for making a gross estimate of crowding out. Both the take-up rate and the rate of crowding out are compared to results found in the literature.

This study is not without caveats. Studies such as Guyer (1990) suggest that unless women are given a more comprehensive set of prenatal care services, reducing the financial barriers alone by expanding Medicaid eligibility will most likely not affect birth outcomes. Gold, Singh, and Frost (1993) indicate that the majority of states have introduced new Medicaid prenatal care programs that offer enhanced prenatal services. Specifically, they report that in 1992, thirty-eight states financially covered at least one augmented prenatal service to Medicaid recipients. There are seven services[67] that fall under the enhanced prenatal services category: 1) care coordination and case management, 2) psychosocial risk assessment, 3) nutrition counseling, 4) health education, 5) psychosocial counseling, 6) home visiting and 7) transportation to a prenatal care provider. Unfortunately, the NMIHS are not rich enough to evaluate the type of enhanced services that may be offered. I only mention these programs to make the reader aware that other policies, aside from the income eligibility expansions, have changed over time.

A second caveat to the validity of these simulations is that they do not account for the widespread shift of Medicaid into managed care. The entire Medicaid climate has changed in the past decade. It is estimated (in 1998) that 54% of the Medicaid population

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[67] Gold, R.B., Singh, S. and J. Frost, "The Medicaid Eligibility Expansions for Pregnant Women: Evaluating the Strength of State Implementation Efforts", *Family Planning Perspectives*, 25(5): 196-207, 1993.

in enrolled in some type of managed care (HCFA, 1999). The transition into managed care not only by the privately insured but particularly by Medicaid clients during this time period (1988-1997) is a natural experiment in itself. Several studies that were discussed earlier (Felt-Lisk & St. Peter, 1997; Rosenbaum, 1997; Welch & Wade, 1995) indicate that the higher quality and different scope of coverage provided to Medicaid clients is due to the transition into managed care. However, Rosenbaum (1997) indicates that many clients are transitioning into "dual" coverage that may actually be less comprehensive. In reality, changes in prenatal care use and health outcomes may be attributed to the transition into managed care rather than to the eligibility expansions themselves. I must stress that this simulation only evaluates the impact of a change in eligibility and nothing else. Nonetheless, this policy simulation sheds light on whether Congress' intent to improve health outcomes via this policy tool can be successful.

As previously mentioned, my results indicate that prenatal care does not impact birth weight. However, depression is shown to have a significant effect on birth weight such that women with a greater number of depressive symptoms bear infants of lower birth weight. This finding may suggest that one effective policy tool for addressing the incidence of low birth weight is to reduce maternal depressive symptoms. In light of this finding, I conduct policy simulations that illustrate the effect of treating depression. Literature has shown that a CES-D score greater than 16 indicates depressive symptoms. Therefore by censoring all CES-D scores that are greater than 16 to only 16 in essence treats women who are depressed. Using the treatment effects model, the policy simulation evaluates the effect of "treating depression" or censoring all CES-D scores to 16 or less on the predicted probability of Medicaid and private insurance, and on the

predicted values on prenatal care and birth weight. The only real difference between the depression simulation and the eligibility expansions simulation is that the depression variable changes rather than the eligibility variable.

Federal legislation on the Medicaid program and eligibility[68]

Medicaid, established in 1965 as Title XIX of the Social Security Act, is a federal-state matching entitlement program that provides medical care for needy individuals and low-income families. While the federal government establishes broad guidelines for Medicaid, each state establishes its own eligibility guidelines, determines the scope of services, sets the rate of payment for services and administers its own program (US DHHS 1997). Since Medicaid is administered by states, Medicaid programs can vary considerably across states. In some instances, an individual who is eligible to receive Medicaid in one state may not be eligible in another state. This is one reason why considerable attention is paid to evaluating the Medicaid program on a state by state basis rather than as a federal program. Nonetheless, several significant changes in federal legislation have taken place in the past two decades that have influenced Medicaid expansions at the state level.

The Medicaid program was initially created as a supplementary medical program to the cash assistance programs for the poor - particularly for children and their mothers. Early legislation forged a strong link between eligibility levels for the Aid to Families with Dependent Children (AFDC) and the Medicaid programs. However, over the course of the past two decades, eligibility has been expanded in two major ways. The first class

of expansions extend eligibility to several groups of non-AFDC individuals, including the medically needy and Medicare beneficiaries, that were not eligible under the initial rules. The second class of expansions increased income eligibility thresholds such that many pregnant women and children under age 19 with incomes above the federal poverty level are now eligible[69].

The first set of Medicaid expansions in the early- to mid-1980s focused on expanding Medicaid to include additional groups of women. Under the initial program rules, only *single* mothers *with* children[70] were eligible. In 1984, Medicaid was expanded to include low-income women pregnant women with their first child (i.e. not yet mothers) as well as to married pregnant women whose husbands were unemployed. The 1984 expansions were extended even further in 1985 when Medicaid was open to all low-income pregnant women regardless of family structure. While these additional groups of women became eligible in the early- to mid-1980s, the income eligibility requirements were still quite stringent. For example, up until 1986, states such as Alabama required that a family's income was restricted to 15.5% of the FPL. This means that for a family of three to be eligible for Medicaid in Alabama in 1986, their income was restricted to $1,414.

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[68] This summary was taken from a variety of papers including Howell, E.M. and Ellwood, M.R. (1991). Medicaid and pregnancy: Issues in expanding eligibility. Family Planning Perspectives. 23(3), 123-128.
69 Since many of the Medicaid eligibility rules are based on a family's income as a percentage of the federal poverty level (FPL), a brief discussion of this is necessary. The FPL or poverty guidelines used for administrative purposes are issued each year in the Federal Register by the US Department of Health and Human Services. While the 48 contiguous states use the same FPL, Alaska and Hawaii each have their own FPL. In addition, not only does the dollar value of the FPL increase each year, the FPL varies by the number of individuals in a household. For example, in 1988, the FPL for a family of three living in one of the 48 contiguous states was $9,690; in Alaska it was $12,110 and $11,150 in Hawaii (Federal Register 1988). In 1998, for a family of three, the FPLs are $13,650, $17,070 and $15,700, respectively. For a family of 8, the FPLs are $27,650, $34,570 and $31,800, respectively. A complete list of the FPLs for all 50 states from 1986-1998 can be found in **Appendix 2.**

The first major income eligibility expansion occurred in 1986. The Omnibus Budget Reconciliation Act (OBRA) of 1986 gave states the option to cover all pregnant women up to 100% of the federal poverty level (FPL). For that same family of three in Alabama, they could earn up to $9,120 and be eligible for Medicaid. One year later in 1987, states had the option of extending eligibility up to 185% of the FPL for pregnant women and for women up to 60 days post-partum. By 1990, a federal eligibility floor was established such that states were required to cover all pregnant women with incomes up to 133% of the FPL. A complete list of state by state Medicaid eligibility guidelines since 1986 can be found in **Table 24**.

During the mid-1980s and early 1990's there were a few significant income-related expansion policies that were implemented as part of the Medicaid program. Until this time, a family's assets were counted as income used in determining eligibility. One policy change that took place was that assets were no longer included in determining eligibility. In essence, this policy raised the income eligibility threshold for families. A second income-related policy was the establishment of the "continuous eligibility" rule. This rule permits a participant to remain on Medicaid for a certain period of time *beyond* which she is eligible for when her income rises above the eligibility threshold. This means that if a woman participated in Medicaid and her income increased (at a future date) beyond the income eligibility threshold, she would still be eligible for Medicaid for a short period of time thereafter. This rule essentially establishes a pseudo grace period. However, it is applied in only three specific situations. The first is that Medicaid covers a woman's entire pregnancy regardless of her change in income (Gold et al. 1993). The

second [and a more recent policy established by the Balanced Budget Act of 1997 Medicaid Provisions] is that an individual under the age of 19 is guaranteed 12 months of continuous Medicaid eligibility once she is determined eligible. Finally, infants are covered for one year beyond the time that the mother is eligible. A third rule that was passed is called presumptive eligibility. This allows a woman easier access to prenatal care. She automatically qualifies for Medicaid covered prenatal care on the spot if she seems likely to qualify. While these expansions are important and have real implications, my analysis only fully captures a change in income eligibility and may not capture these other changes.

Recent waivers

During this era of Medicaid expansions, the Health Care Financing Administration (HCFA) introduced two types of waivers: the Section 1115 waiver or Research and Development waiver and the Section 1915(b) waiver or the Freedom of Choice waiver. The Section 1115 waiver allows states to design budget-neutral, innovative approaches to containing increasing costs as well as expanding Medicaid to the uninsured. The Section 1915(b) waiver permits states to implement Medicaid managed care to the extent that they find it cost-effective, efficient, and not inconsistent with the Social Security Act. The 1915(b) waiver also requires that states must arrange for an independent evaluation (by a state university, etc.) of their managed care program.

[70] With certain exceptions, low-income children under the age of 19 are eligible for Medicaid.

As of June 1998, 17 states have at least one Section 1115 waiver (i.e. some states have multiple programs) and 36 states have at least one Section 1915(b) waiver[71].

The result of these waivers is that Medicaid has been transformed into the managed care climate. As of June 1998, 54% or 16.6 million Medicaid recipients are enrolled in some form of managed care. The Medicaid managed care population has almost quadrupled in numbers since 1993. While some states have over 90% of their Medicaid population in managed care (CO, IA, MT, TN, UT, WA), other states have less than 6% in managed care (AK, LA, SC, WY)[72]. These numbers reinforce the importance of analyzing Medicaid data by state. The hope is that the move to managed care offers the opportunity for states to improve access to and provide higher quality care in established provider networks, as well as contain costs ((Holahan, Zuckerman, Evans, & Rangarajan, 1998). But some are skeptical of an improvement in care and continuity due to dual coverage and carve-outs. That is, managed care organizations (MCOs) may not cover a comprehensive set of services that is equivalent to traditional Medicaid coverage. Therefore, many Medicaid managed care recipients are dually covered. They receive basic coverage from the MCO, but residual services from the state plan. Rosenbaum (1997) argues that this type of dual coverage may be confusing to clients, resulting in clients going without some benefits. While many aspects of Medicaid are changing due to the introduction into managed care, these aspects are not captured in this dissertation.

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[71] States with 1115 waivers are: AL,AZ,CA,DE,DC,HI,KT,MD,MA,MN,NY,OH,OK,OR,RI,TN,VT. States with 1915(b) waivers are: AL,AR,CA,CO,CT,DC,FL,GA,ID,IN,IO,KS,KT,LA,ME,MI,MN,MS,MO,MT,NE,NJ,NM,NY,NC,ND,OR. PA,SC,TX,UT,VA,WA,WV,WI,WY. Health Care Financing Administration (1999, May 10.) National summary of state Medicaid managed care programs as of June 30, 1998. Health Care Financing Administration [Online]. Available: http://www.hcfa.gov/medicaid/nstoc98.htm

[72] Various locations at http://www.hcfa.gov/medicaid/

My data is from 1988 when many of these changes had not yet taken place. Besides, the NMIHS merely indicates whether a woman has Medicaid or not. There would be no way to fully account for any shift toward managed care that may have occurred by 1988. With a richer and more current data set, perhaps these very interesting issues could be addressed.

Federal and state outreach efforts

Along with these tremendous changes in Medicaid, federal Medicaid legislation has focused on improving "real" Medicaid access to women[73]. During the wave of Medicaid expansions, Congress granted states the right to directly enroll eligible women (recipients) in the Medicaid program (Gold, Singh, & Frost 1993). Prior to this policy called outstationing, women were restricted to enroll in the Medicaid program at a state welfare office. While it may not be apparent how this policy increases access to Medicaid, from a pragmatic perspective, it allows an uninsured woman the opportunity to gain access to insurance just by seeking a visit at a health care facility such as a community health center or hospital. While women that participate in AFDC/TANF will already be familiar with Medicaid, many other women may not be aware of their eligibility and would never think that a trip to the state welfare office can provide them with health insurance.

Many states have embraced the opportunity to provide outstationing and other Medicaid outreach programs in order to increase Medicaid caseloads. **Table 5** illustrates these states efforts. By 1992, 36 states engaged in some type of media outreach program while 48 states posted Medicaid eligibility and enrollment information in at least one

location. For the most part, outreach programs entail posting flyers in various locations throughout the state such as churches, hospitals and stores as well as public service announcements on radio and television detailing information on eligibility and ease of enrollment. The goal of these programs is to inform the public that, unbeknownst to them, they may already be eligible to receive Medicaid.

Medicaid eligibility v. take-up rate

One of the primary goals of this dissertation is to evaluate the impact of expanding Medicaid income eligibility on prenatal care and birth weight. However, as several studies have shown, eligibility is not necessarily synonymous with participation. Even if a woman is eligible to receive Medicaid, it does not mean that she participates. In response to this dilemma, the federal government has taken several measures (discussed previously) to reform the Medicaid program so that more women have "real" access. Nonetheless, the problem still persists.

Prior to embarking upon the more rigorous policy simulation, a gross estimate of the Medicaid take-up rate is measured. Recall that the take-up rate is the percent of all Medicaid eligible women who actually participate. If the take-up rate is 100%, then all women who are eligible participate. If the take-up rate is 50%, then only half of all women who are eligible participate. The latter percentage paints a more realistic picture of estimated take-up rates found in the literature.

Using data from the 1988 NMIHS, I calculate the Medicaid take-up (participation) rate for samples of white and black of pregnant women that experienced a live birth. This

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[73] However, none of these programs were really in place by 1988 - the year that the NMIHS was conducted.

analysis requires several steps of calculations[74]. First, women are stratified by state of residence and household size. These are the two primary criteria (along with household income) in determining Medicaid eligibility[75]. Second, each woman's household income is compared to the Medicaid income eligibility level of that household size and state. If a woman's income is no greater than the eligibility threshold, then she is considered to be Medicaid eligible. From these calculations, the percentage of women in the sample that are eligible to receive Medicaid is determined. Finally, for the women that are deemed eligible, it is determined whether or not they participated in Medicaid during their pregnancy. The greater the number of women that were eligible and participated, the higher the take-up rate. Results of these calculations can be found in **Table 25**.

11.5%[76] of white women surveyed in the NMIHS are income eligible to receive Medicaid. Of those who are eligible, 51.4% participate. This means that roughly half of all white women who are eligible to receive Medicaid participate. This rate falls within the scope of other estimates in the literature [see **Table 4**]. For black women, 40.6% are eligible to receive Medicaid. Of those who are eligible, 72.1% actually participate. Proportionally, not only are more black women Medicaid eligible, they are also more likely to participate in the Medicaid program. The first result is not too surprising since black women tend to have lower household incomes than white women do. There are several potential explanations that may explain the second result. One hypothesis is that

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[74] See **Appendix 4** for an example of this calculation.

[75] This estimate is not without error. Another requirement that has been relaxed considerably but still exists to some extent is the assets test. In some cases, a household's assets including an automobile may be used in determining eligibility. The estimate calculated here assumes the assets test away. Additionally, the eligibility guidelines used to calculate this estimate are taken from April 1987 to January 1999. It is plausible that the guidelines used here underestimate eligibility since many of the guidelines are taken from 1987 but eligibility is determined using 1988 data. Cutler and Gruber (1996) also impute Medicaid eligibility and acknowledge the difficulty in doing so without substantial measurement error.

black women may have greater knowledge of the Medicaid program since they traditionally have had a greater propensity to live in low-income households. Another hypothesis may be that black women tend to view the welfare stigma in a different way that white women do. Nonetheless, the take-up rate results indicate that expanding Medicaid eligibility can be an effective means at insuring the uninsured.

Policy simulation I: Expanding Medicaid income eligibility

I conduct a policy simulation to determine whether Medicaid eligibility expansions improve prenatal care utilization and more importantly, infant health outcomes. I utilize the parameter estimates already obtained from the treatment effects model, with birth weight as the infant health measure and onset as the measure of prenatal care, to predict the effect of "turning on" Medicaid eligibility for a newly eligible group of women. Both the black and white models are used. In 1988, the average state Medicaid program covered pregnant women and children whose household incomes did not exceed 100% of the FPL. I expand the eligibility requirements to the 1997 levels (see **Table 24** or **Appendix 3**) and simulate the effects on prenatal care demand and birth weight. By "turning on" Medicaid eligibility for this new group of women one can compare the moments and distributions of the predicted outcome measures before and after the policy change in order to predict the success of the policy.

One important element to note is that expanding Medicaid eligibility to a new group of women does not directly translate into participation by these women. We see this by the less than 100% Medicaid take-up rate. An important feature of the policy

[76] This number suggests that the percent of eligible women is underestimated.

simulation (and a contribution to the literature) is that it does not impose participation on an individual. The simulation only estimates the probability that a woman will participate given more lenient eligibility standards. That is, using the parameter estimates already obtained from previous estimations, the model uses a woman's characteristics to predict the probability is she participates upon becoming eligible. Technically, the model predicts whether a woman participates under the 1988 rules and the 1997 rules, then compares the results in terms of their impact on prenatal care and birth weight. Recognize that the only data that I actually have (and use) from 1997 is the dollar eligibility amount. All of the woman's characteristics are taken from 1988. Below are the series of steps used to conduct the policy simulation. Since the simulation requires many steps, each major step is sectioned off according to the insurance, prenatal care, and birth weight equations. (Note that each step is conducted for both blacks and whites).

Computing the predicted probability of Medicaid and Insurance

The predicted probabilities of Medicaid and insurance illustrate how likely it is that a woman participates in the program, given a vector of her own personal as well as state level characteristics. The simulation here is that one of the state level characteristics is allowed to change over time. Specifically, the dollar income eligibility threshold for Medicaid changes from 1988 (the sample period) to 1997. For example, for a household of three in New Jersey, income eligibility rises from $9,690 in 1988 to $24,661 in 1997. The policy simulation simulates the effect of this increase on the predicted probability that a woman participates in Medicaid or private insurance. It is expected that as income eligibility rises, a woman is more likely to participate in Medicaid but is less likely to participate in private insurance. Results from **Chapter III** confirm this. If in fact overall

Medicaid participation rises while private insurance participation falls, then crowding out occurs.

The first step is to obtain the predicted or fitted values of Medicaid and private insurance from the Stage Two equations of the treatment effects model:

$$\hat{Medicaid}_{1988},\ \hat{Insurance}_{1988}$$

In order to compute the predicted probability of Medicaid and insurance in 1988 (the variables shown above are only the predicted values), the standard normal distribution must be evaluated:

$$\Phi(\hat{\beta}'_{MC}\ X) = \mathbf{Pr}(\hat{Medicaid}_{1988} = 1),\ \Phi(\hat{\beta}'_{PI}\ X) = \mathbf{Pr}(\hat{Insurance}_{1988} = 1)$$

Note that the βs differ between Medicaid and insurance. To compute these probabilities for Medicaid and insurance in 1997, 1988 eligibility must be subtracted from the predicted value, while the 1997 eligibility must be added to the predicted value:

$$\hat{\beta}'_{MC}\ x_{1997} = \hat{\beta}'_{MC}\ x_{1988} - \hat{\beta}_{M1}\ eligibility_{1988} + \hat{\beta}_{M1}\ eligibility_{1997}$$

$$\hat{\beta}'_{PI}\ x_{1997} = \hat{\beta}'_{PI}\ x_{1988} - \hat{\beta}_{P1}\ eligibility_{1988} + \hat{\beta}_{P1}\ eligibility_{1997}$$

Finally, the standard normal distribution of the above can be evaluated and the following obtained:

$$\Phi(\hat{\beta}'_{MC}\ X_{97}) = \mathbf{Pr}(\hat{Medicaid}_{1997} = 1),\ \Phi(\hat{\beta}'_{PI}\ X_{97}) = \mathbf{Pr}(\hat{Insurance}_{1997} = 1)$$

Results[77] from the white model indicate the following:

[77] Note that these probabilities are on the high side. While it is not entirely clear why, one explanation may be that women who are predicted to have Medicaid may have a very high probability (like 0.9) while women who are not predicted to have Medicaid may have a reasonably high probability of (like 0.4). If a cutoff of 0.5 (where probabilities of less than 0.5 are a assigned a 0, probabilities of greater than 0.5 are assigned a 1), then this estimate will be high as seen by my estimates.

$$\Pr(\hat{Medicaid}_{1988} = 1) = .5290, \quad \Pr(\hat{Medicaid}_{1997} = 1) = .6975$$

$$\Pr(\hat{Insurance}_{1988} = 1) = .7653, \quad \Pr(\hat{Insurance}_{1997} = 1) = .7132$$

The probability of participating in Medicaid increased from 52.90% in 1988 to 69.75% in 1997, with an increase of 16.85%. All of the simulation results can be found in **Table 26**. The eligibility expansions are predicted to have a huge effect on increasing participation in Medicaid. Recognize that the expansions are targeted at low-income individuals who are not currently insured. If women who were previously uninsured accounted for the full 16.85% increase, then increasing eligibility is the appropriate policy tool to use in order to alleviate uninsurance in the US. However, at the same time that Medicaid rose, the probability of having private insurance fell from 76.53% in 1988 to 71.32% in 1997, or a decrease of 5.21%. This result reveals that part of the increase in Medicaid may be due to a decrease in private insurance. This is crowding out. Specifically, 30.92%[78] of the increase in Medicaid may be due to crowding out. In a sample from the March Current Population Surveys (CPS) from 1988-1993, Cutler and Gruber (1996) estimate the rate of crowding out to be 31%. This rate is identical to the rate computed here. In a related paper using the CPS as well, Dubay and Kenney's (1997a) estimate of crowding out is 45%. While my estimate is quite similar to both of these papers, my estimate is only for a sample of white women whereas both of theirs include a mix of races.

Results from the black model are the following:

$$\Pr(\hat{Medicaid}_{1988} = 1) = .6645, \quad \Pr(\hat{Medicaid}_{1997} = 1) = .8020$$

$$\Pr(\hat{Insurance}_{1988} = 1) = .6031, \quad \Pr(\hat{Insurance}_{1997} = 1) = .5343$$

These results indicate that, in general, a greater percentage of black women (than white women) are likely to participate in Medicaid, while a greater percentage of white women are likely to have private insurance. Possible hypotheses discussed earlier were that demographics such as income, education, and industry may account for much of the difference. Also, the welfare stigma may be regarded as a different cost to black women than white women or black women may be more aware of welfare programs, increasing the probability of Medicaid participation. Medicaid participation is predicted to rise from 66.45% in 1988 to 80.20% in 1997, with an increase of 13.75%. The probability of having private insurance fell from 60.31% in 1988 to 53.43% in 1997, with a decrease of 6.88%.

These estimates indicate that 50.03% of the increase in Medicaid participation may be due to a decrease in private insurance participation. This illustrates that the crowding out rate is larger for blacks than for whites. Such a large rate of crowding out signals a few different possibilities. Stratifying the sample by race may be very revealing. When the white and black rates of crowding out are simply averaged, the overall crowding out rate is 40.48%. This estimate falls in between the one found by Cutler and Gruber (1996) and the one computed by Dubay and Kenney (1997a). Therefore, it is possible that the rates computed here are on par with others in the literature. But why are blacks much more likely to drop their private insurance than whites? For one thing, these are only rough estimates of crowding out using only the most simplistic of eligibility rules. It is possible that a more detailed account of the eligibility rules would yield different results. However, it is plausible that blacks, in general, are in lower paying

[78] This percentage is computed by the following: 5.21/16.85 = 30.92.

industries and occupations, where the private insurance plans offered are less generous than in higher paying industries. This suggests that policies should be targeted at lower-income workers who are marginally accessible to private insurance. One example of a policy might be to increase the incentives to this population to maintain a private insurance plan. The state Medicaid program could partially subsidize private insurance premiums. For example, if Medicaid expects to spend $500 per year on each client, then the Medicaid program may be willing to subsidize insurance premiums by $100 per "potential" client in order to keep caseloads down.

Computing the predicted values for the onset of prenatal care

This next phase of the policy simulation is to predict the onset of prenatal care under the 1988 and 1997 eligibility rules and compare their predictions. Differences between the two predictions may be attributed to the indirect effect from the change in eligibility on the predicted probabilities of Medicaid and private insurance.

The first step in this section of the simulation is to obtain the predicted value of the onset of prenatal care from the onset equation in the Final Stage of the treatment effects model:

$$\hat{Onset}_{1988}$$

This value can be obtained from the following equation:

$$\hat{Onset}_{1988} = \hat{Onset}_{1988} - \hat{\beta}_{O1}\, Medicaid - \hat{\beta}_{O2}\, insurance - \hat{\beta}_{O3}\, \lambda^{MC} - \hat{\beta}_{O4}\, \lambda^{PI} + \hat{\beta}_{O1}\, \mathbf{Pr}(\hat{Medicaid})_{1988} + \hat{\beta}_{O2}\, \mathbf{Pr}(\hat{Insurance})_{1988}$$

In order to account for the predicted probabilities of Medicaid and private insurance that were previously constructed, the actual values of Medicaid and private insurance along

with their associated inverse Mills ratios must be subtracted from the predicted value of the onset of care while the new predicted values are added. Notice that the coefficients on the predicted probabilities of Medicaid and insurance are the same coefficients as the ones on the actual Medicaid and insurance variables. The original coefficients are used so that the model is not re-estimated. Similarly, the predicted value of onset in 1997 can be computed replacing the 1988 predicted values with the 1997 predicted values:

$$\hat{Onset}_{1997} = \hat{Onset}_{1988} - \hat{\beta}_{O1}\, Medicaid - \hat{\beta}_{O2}\, insurance - \hat{\beta}_{O3}\, \lambda^{MC} - \hat{\beta}_{O4}\, \lambda^{PI} + \hat{\beta}_{O1}\, \mathbf{Pr}(\hat{Medicaid})_{1997} + \hat{\beta}_{O2}\, \mathbf{Pr}(\hat{Insurance})_{1997}$$

The white results from this stage of the policy simulation reveal the following:

$$\hat{Onset}_{1988} = \mathbf{8.3734},\ \hat{Onset}_{1997} = \mathbf{8.4309}$$

The predicted value of onset increased from 8.37 weeks in 1988 to 8.43 weeks in 1997, with an overall increase of less than half of a day. While an increase in the onset of care is an adverse outcome, there is no "real" increase here. The difference suggested here is about a dramatic as having an afternoon appointment rather than a morning appointment. The results shown thus far suggest that as eligibility becomes more generous and moves more women into Medicaid and fewer women into private insurance, the onset of prenatal care begins at relatively the same time. Increasing eligibility to whites has no real effect on the onset of prenatal care.

The black results are as follows:

$$\hat{Onset}_{1988} = \mathbf{9.7840},\ \hat{Onset}_{1997} = \mathbf{9.4979}$$

The predicted value of onset decreased from 9.78 weeks in 1988 to 9.50 weeks in 1997, with an overall decrease of roughly 2 days. It is clear that the impact of eligibility is

greater for blacks than whites and is of some limited policy significance. While a decrease of two days suggests that a woman may seek care earlier in the week rather than later in the week, this result may also suggest that more generous eligibility expansions may reduce the onset of care further for blacks. Most interesting to note is that blacks begin prenatal care almost an entire week later than whites, on average. Therefore, an increase in eligibility seems to level the playing field a bit for blacks. This is certainly a result of policy interest. It would be interesting to track this statistic as eligibility expands over time.

Computing the predicted values for birth weight

The final phase of the policy simulation is to compare the predicted values of birth weight before and after the eligibility expansion. The difference in the predicted birth weight may be attributed not only to the predicted probabilities of Medicaid and insurance but also to the new predicted time of onset. This is the primary reason for conducting the simulation (or advancement over simply dropping in eligibility into a birth weight equation) - to capture both the direct and indirect means at which a change in eligibility may effect birth weight.

A similar procedure (to the onset procedure) is used to predict the 1988 and 1997 values of birth weight. The only real addition to this section (versus the computation of predicted onset) is that the actual onset of prenatal care must be subtracted and the predicted value of onset must be added to birth weight. The computation of predicted

birth weight in 1988 is given below:

$$\hat{Birthweight}_{1988} = \hat{Birthweight}_{1988} - \hat{\beta}_{B1}\, Medicaid - \hat{\beta}_{B2}\, insurance - \hat{\beta}_{B3}\lambda^{MC} - \hat{\beta}_{B4}\lambda^{PI} + \hat{\beta}_{B1}\hat{Medicaid}_{1988} + \hat{\beta}_{B2}\hat{Insurance}_{1988} - \hat{\beta}_{B5}\, onset + \hat{\beta}_{B5}\hat{onset}_{1988}$$

Similarly, the predicted value of birth weight in 1997 can be computed by the following:

$$\hat{Birthweight}_{1997} = \hat{Birthweight}_{1988} - \hat{\beta}_{B1}\, Medicaid - \hat{\beta}_{B2}\, insurance - \hat{\beta}_{B3}\lambda^{MC} - \hat{\beta}_{B4}\lambda^{PI} + \hat{\beta}_{B1}\hat{Medicaid}_{1997} + \hat{\beta}_{B2}\hat{Insurance}_{1997} - \hat{\beta}_{B5}\, onset + \hat{\beta}_{B5}\hat{onset}_{1997}$$

The white results from the final stage of the policy simulation reveal the following:

$$\hat{Birthweight}_{1988} = 3001.8175,\ \hat{Birthweight}_{1997} = 2951.3537$$

The predicted value of birth weight decreased from 3001.82 in 1988 to 2951.35 in 1997, with an overall decrease of 50.47 grams. While this result seems shocking at first since birth weight actually declines, it is not so shocking in light of the fact that other results in this dissertation have shown that Medicaid participation seems to lead to adverse outcomes. Favorable results, however, are indicated by an increase in birth weight in the black population. The black results are the following:

$$\hat{Birthweight}_{1988} = 2867.6499,\ \hat{Birthweight}_{1997} = 2888.7561$$

For blacks, the predicted birth weight increased by 21.11 grams. This means that an increase in Medicaid eligibility leads to an increase in black birth weights.

The results generated thus far in the policy simulations are quite interes ting. While an increase in Medicaid eligibility reduces the onset of care and increases birth weight for blacks, both favorable outcomes, the results are essentially opposite for whites. Congress' intent to improve care and health outcomes via Medicaid eligibility expansions seem to be reflected in the black population but not the white population. This could be due to crowding out.

Policy simulation results according to eligibility status in 1988 and in 1997

The results so far indicate that expanding Medicaid eligibility leads to more favorable outcomes for blacks but less favorable outcomes for whites. Since this result is a bit difficult to explain, results from the eligibility policy simulations are broken down further according to several key groups.

This first set of results is stratified according to a woman's Medicaid eligibility status in 1988 and in 1997. Specifically, three groups of women are identified: women who were eligible to receive Medicaid in 1988, women who were eligible to receive Medicaid in 1997 but were not eligible in 1988, and women who were not eligible in 1997. The results are summarized in **Table 26**. The following results are for white women. 11.48% of women fall into the first group, 17.25% fall into the second group, and the remaining 71.27% of women fall into the third group, respectively. The simulation results are of greatest interest for the second group since this is the group most affected by the eligibility expansion. Recall that this group of women was not eligible in 1988 but became eligible in 1997. Results indicate that the onset of care decreased from 9.11 weeks to 8.99 weeks (i.e. less than 1 day) from 1988 to 1997, but that birth weight declined from 2982.11 to 2955.01 grams (or 27.1 grams). The eligibility expansion

seemed to have a favorable effect on the onset of care, although quite a modest effect, but an adverse effect on birth weight.

Are the expansions predicted to have had any effect on those who were already eligible in 1988? The answer is an overwhelming yes. Not only is Medicaid participation predicted to increase by over 13 percentage points, but also the onset of care fell by over 2 days and birth weight increased by over 21 grams. A possible explanation here is that the increase in expansions made women who were already eligible for Medicaid aware of their eligibility and that the Medicaid expansions seem to most favorably affect lower-income women. This result is further supported by results from the third group of women: women who were not eligible in 1997. The expansions are predicted to increase the onset of care and reduce birth weight for this group of women, both adverse outcomes. The overall policy simulation results discussed earlier (that indicate that the expansions have little or even an adverse effect on white women) are not revealing the true effect of the expansions. The expansion effects on lower-income (first group) and higher-income (third group) women most likely cancelled each other out. These results are consistent and likely reveal that the Medicaid expansions do favorably affect low-income women. The policy implications here are that a) the expansions are targeting and affecting the population that Medicaid was meant for and b) Medicaid is improving prenatal care utilization and health outcomes for this targeted population, but c) due to crowd-out, there may be some adverse outcomes in upper income groups.

The favorable results shown for white women are enhanced even further for black women. 40.60%, 23.69%, and 35.71% of black women fall into the first, second, and third group (defined earlier), respectively. Proportionally, there is a much larger group of

black women eligible to receive Medicaid. In some sense, this makes black women a more targeted group since they are more likely to be living in low-income households. Both the first and second eligibility groups are predicted to experience a modest decrease in the onset of care and an increase in birth weight. Specifically, for the first group, the simulation predicts a decrease in the onset of care by over 3 and half days and an increase in birth weight by over 71 grams. For the second group, onset is reduced by over 2 and a half days and birth weight increases by over 30 grams. Adverse outcomes are shown for the third (highest-income) group.

Expanding Medicaid income eligibility seems to improve prenatal care utilization and infant health outcomes for low-income white women and low/moderate-income black women. The expansions have an adverse effect on women who are not Medicaid eligible. It would be interesting to know whether all ineligible women experience adverse health outcomes or if it is only the women who are marginally ineligible. Roughly 5% of whites and 10% of blacks in the highest-income group (third group) are predicted to drop their private insurance coverage from 1988 to 1997.

Medicaid eligibility policy simulation results stratified by low birth weight

This next set of policy simulation results is stratified by whether a woman had a low birth weight or a normal birth weight infant. Recall that low birth weight is defined as an infant weighing less than 2500 grams or 5.5 pounds. Generally, the results indicate that for black women with both low and normal birth weight infants that the eligibility expansions reduced the onset of care and increased birth weight. The results are opposite for white women. Since the eligibility expansions seem to affect low and normal birth weights in the same way, there is no real result to discuss here. These results, however,

do provide further evidence that black women are more favorably affected by the expansions than white women are.

Pure reduced-form birth weight computations

The policy simulations are conducted in order to capture both the direct and indirect effects of a policy change. Currie and Gruber (1996b) take a different approach at evaluating Medicaid eligibility policy. Using aggregate data, they estimate reduced-form models that evaluate the effect of Medicaid eligibility on the incidence of low birth weight and infant mortality. They construct eligibility in three different ways. First, they simulate eligibility for all women in 1979. Second, they simulate eligibility for women who were eligible in 1992 but not eligible in 1979. Third, they simulate eligibility for women who were not eligible in 1986 but who became eligible in 1992, using Medicaid rules rather than AFDC rules that are more restrictive. Recall that the results from their models indicate that expanding eligibility decreased the incidence of low birth weight. These results are most significant when eligibility is defined in the second way.

Recall that in the previous chapter, I also estimate a pure reduced-form birth weight equation. The regression results from this model are discussed in the previous chapter. However, this model can also be used to generate policy simulations, albeit in a more simplistic manner. Since eligibility enters directly into the birth weight equation the gross effect of a change in eligibility can be captured and compared to Currie and Gruber's results. The pure reduced-form equation includes only all of the exogenous variables in the system and is defined by the following:

6. $$Birthweight = \beta_1 + \beta_2 ability + \beta_3 environmental + \beta_4 anthropometric + \beta_5 maternal + \beta_6 fertility + \beta_7 demographics + \beta_8 income + \beta_9 cohab + \beta_{10} CESD^{avg} + \varepsilon^{rfBWT}$$

Recall that ***eligibility*** is embedded within the ***ability*** grouping of variables. In order to simulate the effect of an eligibility expansion, the predicted values of birth weight must be compared before and after the simulation. The predicted value of birth weight in 1988 can be predicted directly from the equation above. However, in order to predict birth weight in 1997, 1988 eligibility must be subtracted and 1997 eligibility must be added to the predicted value of birth weight. The following equation computes the predicted value of birth weight in 1997:

$$\hat{Birthweight}_{1997} = \hat{Birthweight}_{1988} - \hat{\beta}_{B1}\, eligibility_{1988} + \hat{\beta}_{B1}\, eligibility_{1997}$$

The white and black birth weight predicted values for 1988 and 1997 are the following:

Whites: $\hat{Birthweight}_{1988} = 3131.4176$, $\hat{Birthweight}_{1997} = 3194.5206$

Blacks: $\hat{Birthweight}_{1988} = 2953.1026$, $\hat{Birthweight}_{1997} = 2960.6296$

Somewhat consistent (although not entirely) to the results generated by the treatment effects model, both white and black birth weights rose as a result of an increase in eligibility. White birth weight is predicted to increase by 63.10 grams while black birth weight is predicted to increase by a more modest 7.53 grams. Recall that results from the treatment effects model illustrated that overall only black birth weights increased. However, for low-income white women, the eligibility expansion also led to an increase in birth weight. The results shown here are a direct result of the increase in eligibility since no other variable changed. Taken as a whole, the Medicaid eligibility policy simulations do provide fairly robust evidence that an eligibility expansion may lead to an increase in birth weights. This result is somewhat consistent with Currie and Gruber

(1996b). However, my model is an improvement over theirs since it takes into account all of the different channels in which eligibility may affect outcomes. In doing so, it allows for both linear and non-linear effects to be captured.

Policy simulation II: Treating depression

One of the findings in this dissertation is that depressed black women have lower birth weight infants, ceteris paribus. Taken one step further, a policy recommendation may be to suggest that reducing the incidence of depression may yield more effective prenatal care utilization and better health outcomes. However, this finding is not consistent across all of the models presented. Yet it does inspire additional research to address the question in another way. Consequently, I conduct a policy simulation that essentially "treats" depressed women of their depressed symptoms and then simulates that impact on Medicaid and private insurance participation, the onset of prenatal care, and most importantly birth weight.

Technically, an identical process to that of the Medicaid eligibility simulation is conducted for the depression simulation. Very generally recall that in the eligibility simulation the 1997 eligibility rules were simulated on the sample of women. Means of the key variables were then compared across the 1988 rules and the 1997 rules. Whereas the eligibility simulation used 1997 eligibility rules, the depression simulation creates a variable to represent the "1997 state of the world" for each women. That is, if a woman's CES-D score is 1988 was less than or equal to 16 (i.e. suppose $CES\text{-}D_{woman\ 1} = 7$), her 1997 CES-D score is the same as it was in 1988 (i.e. $CES\text{-}D_{woman\ 1} = 7$). If a woman's CES-D score in 1988 was greater than 16 (i.e. $CES\text{-}D_{woman\ 2} = 25$), her 1997 CES-D score

is censored (or equals) 16 (i.e. $CES\text{-}D_{woman\ 2} = 16$). This censoring is what I consider treatment for depression.

Treatment of depression policy simulation results

Results from the depression simulation can be found in **Table 27**. 14.83% of white women and 28.30% of black women were "treated" in 1997. That is, these women's CES-D scores were greater than 16 in 1988 and censored to equal 16 in 1997. Keep in mind, though, that this is only a mechanical process and that these women are not actually cured. By treating these women of their depressed symptoms, the mean CES-D score for whites fell from 8.79 in 1988 to 7.75 in 1997. For blacks, the mean CES-D score fell more substantially from 12.84 in 1988 to 10.60 in 1997. The question that the simulation attempts to address is whether treating these women lead to the earlier onset of prenatal care and to higher birth weight infants. The simulation also reveals the relative participation in Medicaid and private insurance over the sample time period. Only the results pertaining to the treated population (with CES-D scores greater than 16), a subset of the white and black samples, are discussed.

The results for white women suggest first that treating depression yields an opposite effect on insurance/Medicaid participation than increasing Medicaid eligibility. The depression simulation reveals that Medicaid participation is predicted to decrease from 0.59 in 1988 to 0.54 in 1997 while private insurance coverage slightly increased by one percentage point from 0.68 in 1988 to 0.69 in 1997. The relative change in both Medicaid and private insurance coverage is somewhat negligible though. The remainder of the results indicates that both the onset of care and birth weight increase as a result of treating depression. Specifically, the onset of care increases by about 1 day from 9.17

weeks in 1988 to 9.32 weeks in 1997. Remember that this is an adverse result. One would have hypothesized that onset would decrease as a result of treating depression. This is shown in the regression results. One possible explanation is that women may perceive prenatal care as just another type of medical care. It's plausible to imagine that a depressed woman might seek depression treatment from a prenatal care provider, particularly if she did not have a relationship with a primary care physician. Therefore, if she "instantaneously" becomes cured of her depressive symptoms then she may not feel the urgency to seek prenatal care early. An alternative explanation is that the effect of Medicaid is confounding the effect of treating depression. Remember that the simulation captures all of the channels in which treating depression can affect birth weight. Since the regression results indicate that Medicaid adversely affects outcomes, it is possible that the presence of Medicaid here is causing depression treatment to be ineffective in terms of reducing the onset of care. The depression simulation also reveals a modest increase in birth weight from 2877.92 grams in 1988 to 2882.45 grams in 1997 (a 4.5 gram increase).

While the white results are mixed in terms of improving outcomes, black women seem to reap greater benefits from being treating for depressive symptoms. The onset of prenatal care is predicted to decrease from 10.38 weeks in 1988 to 10.17 weeks in 1997, a decline of approximately a day and a half. Intuitively, this result makes sense. Literature has shown that depressed individuals have difficulty performing simple daily tasks. Therefore, one might expect that the "state of depression" would act as a barrier to seeking prenatal care. If that barrier is removed, one might expect that earlier and adequate care would become more viable. While a reasonable hypothesis can be formulated to explain both earlier and later prenatal care, it is difficult to explain why

treated white women seek later care and why treated black women seek earlier care. Easier to explain is the increase in birth weight from 2805.27 grams to 2868.52 grams or an increase of 63.25 grams. This seems to indicate that treating depression in both white and particularly in black women improves infant health outcomes. To date, no other research has found this result. This research is consistent with findings that depressed women can pass along depressed symptoms in terms of reduced brain activity to their infants. Not only is this one of the most important findings in this dissertation, it is a promising avenue for future research and suggests certain policy recommendations. It may be that one way to reduce the incidence of lower birth weight is to assess a woman's mental health status at the time of her first prenatal visit and consequently treat any depressed women before they give birth.

Treatment of depression policy simulation results stratified by low birth weight

The depression policy simulation results are also stratified by whether the woman had a low birth weight or normal birth weight infant. Overall the results indicate that for white women, the onset of care slightly increased and birth weights increased for the low birth weight population but decreased for the normal birth weight population. This seems to indicate that the policy simulation is more effective in the low birth weight sample. For black women, the onset of care declines and birth weights rose. These results suggest that stratifying by low and normal birth weight does add some new information. Additionally, black women tend to reap greater benefits from being treated for depression than white women.

Conclusion

The primary reason for conducting policy simulations is to capture both the direct and indirect effects of a policy change. This technique is a nice complement to regression-based techniques when complex relationships are modeled since it captures all of the different ways that a policy can affect an outcome. The overall findings from the eligibility simulations suggest that an expansion in Medicaid eligibility reduces the onset of prenatal care for low-income whites and low- to middle- income blacks and that birth weights are predicted to rise for these same demographic groups. In general, the magnitude of the effects appears to be larger on average for black than for whites. The depression simulation reveals that treating depression leads to an increase in the onset of care for whites but a decrease in the onset of care for blacks. Birth weight is predicted to rise for both treated white women and black women, with the magnitude again larger for blacks. When the eligibility and depression simulation results are stratified by low birth weight, the depression simulation reveals that birth weights are predicted to increase for white women who have low birth weight infants. Otherwise, this breakdown adds no new information. Reduced-form eligibility simulations reveal that the eligibility expansion favorably affects black and white women. Finally, the crowding out of private insurance by Medicaid is evident in both the white and black populations.

The policy simulation contributes several different findings to the literature. The first is that separate crowding out estimates are obtained for both white and black samples of women. For whites, crowding out is estimated to be 30.92% and for blacks it is estimated at 50.04%. While these estimates fall with the range of other estimates in the literature, it appears as though blacks crowd out at a higher rate than whites. Medicaid

take-up rates computed in this dissertation also reveal that blacks have a greater tendency to take-up Medicaid upon becoming eligible. One possible hypothesis that may explain why blacks are more likely to participate in Medicaid than whites is that they are more likely to live in low-income households. This can be seen in the NMIHS sample where the mean income of whites is almost twice as high as it is for blacks. As a result, blacks may be more aware of the Medicaid eligibility guidelines. Another potential hypothesis may be that black women regard the welfare stigma as a relatively low cost associated with participating in a welfare program. These are only two suggested hypotheses. Unfortunately, the data do not provide any additional guidance in interpreting these results.

The next finding from this policy simulation reveals that expanding Medicaid eligibility leads to favorable health outcomes for poorer- to middle- income women but leads to adverse health outcomes for higher-income women. Since the Medicaid program is designed to target and assist women and children who live lower-income households, one might say that the expansions were successful at improving outcomes. It should not necessarily be expected that expanding Medicaid eligibility would improve health outcomes for higher-income women. However, it is surprising that the expansions lead to adverse outcomes for higher-income women. One explanation may be that this is a result of crowding out.

Overall, both the eligibility and depression simulations reveal more favorable outcomes for blacks, albeit in certain circumstances, white women also experienced favorable outcomes. While it is unclear why black women respond more favorably to the eligibility expansions and to depression treatment, there are several policy implications

that arise. Particularly for blacks, there is evidence of an intergenerational transfer of depressive symptoms from mother to child. Consequently, women should be given a mental health assessment at their first prenatal care visit. Upon diagnosing depressive symptoms, women should be given immediate treatment as part of her prenatal care program in order to reduce the adverse effects that may be passed on to her infant. Results from the eligibility expansions seem to suggest that enrolling lower-income women, particularly black women, in the Medicaid program leads to more favorable outcomes. This seems to suggest that outreach programs should be continued and perhaps even expanded. Outreach efforts should not neglect to reach low - to middle - income women. Though such efforts may lead to crowd-out and thus worsen outcomes for higher-income women.

CHAPTER V

CONCLUSION

This dissertation seeks to answer several questions regarding the correlates of infant health such as prenatal care, Medicaid, private insurance, and depression. In doing so, two major contributions are made. The first major contribution highlights the importance of including Medicaid and private insurance into the health production function framework. Medicaid and private insurance are treated as endogenous or choice inputs in the production of infant health. I assume that a woman chooses the type of insurance coverage that maximizes her own utility and infant health. By including insurance type directly into the infant health production function the quality effects that Medicaid and private insurance have on infant health can be directly captured. In addition, the effects of the Medicaid eligibility rules on both kinds of coverage are considered since it is expected that these rules influence the type of insurance coverage demanded. Policy simulations that evaluate the effect of the Medicaid expansions on insurance choice, prenatal care, and infant health further illustrate the necessary role that Medicaid and private insurance coverage have within the health production function framework. The second major contribution highlights the importance of including maternal depression as an input in the health production process. Recent depression studies within the health and epidemiological literature reveal that a) depressed

individuals experience poorer day-to-day functioning and well-being than non-depressed individuals and that b) there is evidence of an intergenerational transfer of depressive symptoms from mother to infant. In light of these studies, the question of whether a depressed woman may demand a sub-optimal quantity of prenatal care or level of insurance coverage, either of which may affect infant health is explored. In addition, by entering depression directly into the health production function, one can explore whether there is an intergenerational transfer of depressive symptoms from mother to child as measured by reduced birth weight. Finally, whether treating depression improves outcomes is also explored. The effects of "mechanically" reducing depressive symptoms (by reducing a woman's depression score) are simulated on insurance choice, prenatal care, and birth weight.

The effects of Medicaid and private insurance on prenatal care and infant health are seen throughout the theoretical and empirical models and in the policy simulations. In the theoretical model of health production, I assume that the woman's type of health insurance coverage affects her overall utility, indirectly through the budget constraint and directly through welfare stigma and through quality effects. Since three different types of insurance coverage are considered here, no insurance/self-pay, Medicaid, and private insurance, three utility maximization problems are derived. For simplicity, in the theoretical model, all women are assumed to be Medicaid eligible and women can choose to be privately insured, participate in Medicaid, or be uninsured. However, in the empirical model, Medicaid dollar income eligibility is considered exogenous. While I assume that women can adjust their income to become Medicaid eligible or seek a job that provides private insurance, women cannot affect state level Medicaid eligibility.

The empirical treatment effects model evaluates the direct effects that Medicaid and private insurance have on birth weight while at the same time controlling for self-selection. By including Medicaid and private insurance as inputs directly into the health production function the relative quality effects can be captured. The policy simulations further predict the effects of Medicaid on the key variables. Using the parameters estimated from the treatments effects model (with my original 1988 data), I simulate the effects of expanding Medicaid eligibility according to the 1997 rules.

The Field model of health determinants suggests that several different factors including genetics, the environment, medical care, the population, and lifestyle all affect health. My results consistently show that early and frequent prenatal care do not have a statistically significant impact on infant health in terms of birth weight or the incidence of low birth weight. In light of the Field model, this result is not too surprising, although a bit disappointing. However, results indicate that women with Medicaid have lower birth weight infants. This may suggest that Medicaid provides inferior quality care than either private insurance or self-payment. Across the board a woman's anthropometric characteristics strongly affect birth weight. In addition, indicators of a woman's lifestyle including smoking also affect birth weight. This suggests that much can be determined about the birth weight of an infant from a woman's own physical structure (such as her own birth weight and her own height) as well as from her lifestyle and behaviors. These results all indicate that some aspects of infant health cannot be directly affected by policy (anthropometry matters), while other aspects may be affected, but in a different manner than we may have thought.

While the treatment effects model evaluates the direct effect of Medicaid and private insurance on birth weight, the policy simulations predict the effect of a temporal change in Medicaid eligibility on birth weight. The overall findings from the eligibility simulations suggest that an expansion in Medicaid eligibility reduces the onset of prenatal care for low-income whites and low- to middle- income blacks and that birth weights are predicted to rise for these same demographic groups. In general, the magnitude of the effects appears to be larger on average for blacks than for whites. One explanation for this is that black women are more likely to comprise the population that is targeted by the eligibility expansions (i.e. low income single women with children). Reduced-form eligibility simulations also reveal that the eligibility expansion is predicted to increase birth weights for both blacks and whites. Finally, the crowding out of private insurance by Medicaid is evident in both the white and black populations. This may suggest some evidence that Medicaid is of lower quality than private insurance.

The effects of depression on Medicaid and private insurance participation, prenatal care, and infant health can also be seen throughout the models and policy simulations developed in this dissertation. The original intent behind incorporating depression into the framework was to estimate its impact on insurance choice, prenatal care and infant health. It is assumed that a depressed mom may select into a sub-optimal type of insurance or demand a sub-optimal amount of prenatal care, and that her depressed state may affect the health of her infant. However, it was realized that depression may not only be an exogenous input into the production process but it may also be an output. Post-partum depression is the most common example of this output. In light of this, I consider the exogenous type of depression to reflect a woman's longer-

term mental health state while the endogenous component reflects transitory depression. In the theoretical model, depression is modeled as both an input in prenatal care demand and in health production and as a output of a production process. However, due to data constraints, only the exogenous component of depression is reflected in the empirical model. While the effects of depression on the key variables are captured in the treatment effects model, the predicted effects of "treating" depression or reducing depressive symptoms in women are captured in the policy simulation.

This is the first study to recognize a woman's state of mental health in the context of the health production function. Depression is found to significantly affect Medicaid and private insurance participation, the number of visits obtained during the pregnancy, but most importantly, birth weight in some of the model specifications. Results suggest that a higher depression score may lead to a reduction in birth weight. While other studies have shown that an intergenerational transfer of depressive symptoms, in the form of reduced brain activity, from mother to newborn, this is the first study to suggest that depression may also affect birth weight. The depression simulation reveals that treating depression leads to an increase in the onset of care for whites but a decrease in the onset of care for blacks. Birth weight is predicted to rise for both treated white women and black women, with the magnitude again larger for blacks.

In general, this dissertation makes a relatively substantial contribution to the economics literature by illustrating the importance of including depression and expanding the role that Medicaid plays in the health production function framework. Results suggest that different types of health insurance including Medicaid, private insurance, and having no insurance, exhibit quality differences in the key outcomes. The eligibility

simulation shows that there is room for policy in improving health outcomes particularly for lower-income women. Additionally, depression is found to have effects throughout the treatment effects model. The depression simulation also reveals the potential for policy to affect the key outcomes, most importantly, infant health.

Table 1. Summary of variables included in the economic models of prenatal care and birth weight

Study	Mother's anthropometric characteristics	Medicaid/ private insurance included?	Other Endogenous variables?	Prenatal care	Selection?	Stratifies by race?
Rosenzweig & Schultz (1982, 1983)	--	--	Mother's age, smoking, # of previous live births	Treated an endogenous	--	No - race is included as a regressor
Grossman & Joyce (1990)	--	Medicaid dummy variable in prenatal care equation - treated as exogenous	--	Treated as endogenous	Estimate a live birth probit and create an inverse Mills ratio	Yes
Rosenzweig & Wolpin (1991)	Weight gain	--	--	Treated as exogenous	--	No - race is included as a regressor
Joyce (1994)	--	Medicaid/insurancedummy variables in prenatal care equation - both variables treated as exogenous	--	Treated as endogenous	Estimates a live birth probit and creates an inverse Mills ratio	Yes, by white, black, and hispanic
Warner (1995)	--	Medicaid/self-pay dummy variables in prenatal care equation - both variables treated as exogenous	--	Treated as endogenous	--	Only evaluates black births
Warner (1998)	Mother's height, pre-pregnancy weight, own birth weight, pregnancy weight gain (adjusted for gestation)	--	--	Treated as endogenous	Warner believes that an even greater problem than the existence of pregnancy selection effects is whether these effects differ systematically between population subgroups, particularly race. He stratifies by race and includes "pregnancy wantedness" variables to control some of the selection effect.	

continued on next page

Study	Mother's anthropometric characteristics	Medicaid/ private insurance included?	Other Endogenous variables?	Prenatal care	Selection?	Stratifies by race?
Currie & Gruber (1996b)	--	Medicaid eligibility in aggregate low birth weight/infant mortality equations - treated as exogenous and instrumented		--	--	No - use % white (i.e. aggregate not individual level data)
Joyce (1997)	--	Augmented Medicaid prenatal care program in birth weight/LBW equations - treated as exogenous and endogenous			--	No - race is included as a regressor
Currie & Thomas (1995)	--	Medicaid/insurance dummy variables in child well-visits equations - both variables treated as exogenous	Well visits are the equations of interest (i.e. paper doesn't look at health outcomes) - visits are endogenous		--	No - but all exogenous variables are interacted with black and white dummy variables

Table 2. Measures of infant health or birth weight found in the literature

Measurement	Found or cited in ...
Actual birth weight in grams	Rosenzweig and Schultz (1982, 1983) Grossman and Joyce (1990) Rosenzweig and Wolpin (1991) Joyce (1994) Joyce (1997) Warner (1995, 1998)
Birth weight adjusted for fetal growth and gestation: $\frac{\textit{actual birthweight}}{\hat{\textit{birthweight}} = \hat{\beta}_0 - \hat{\beta}_1(\textit{weeks}) + \hat{\beta}_2(\textit{weeks})^2 - \hat{\beta}_3(\textit{weeks})^3}$	Rosenzweig and Schultz (1982, 1983)
Gestation in weeks	Rosenzweig and Schultz (1982) Rosenzweig and Wolpin (1991)
Dichotomous measure (0,1) of low birth weight (LBW) which is defined as birth weight < 2500 grams	Joyce (1997)
Dichotomous measure (0,1) of very low birth weight (VLBW) which is defined as birth weight < 1500 grams	Joyce (1997)
Dichotomous measure (0,1) of term low birth weight (termLBW) which is defined as birth weight < 2500 grams and gestation > 37 weeks	Joyce (1997)
Neonatal mortality rate	Corman and Grossman (1985) Corman, Joyce, and Grossman (1987)

Table 3. Measures of prenatal care found in the literature

Measurement	Found or cited in...
Delay (since conception) in seeking prenatal care (in months, days)	Rosenzweig and Schultz (1982, 1983) Grossman and Joyce (1990) Joyce and Grossman (1990) Warner (1995, 1998) Liu (1998)
Standardized number of prenatal visits, adjusted for gestation: $15 \times \frac{\textit{actual \# of prenatal visits}}{\textit{ACOG recommended \# of prenatal visits adjusted for gestation}}$	Warner (1995, 1998)
Interaction term that measures the degree of substitution or complementarity between delay and the number of visits: $\frac{\textit{adjusted \# of prenatal visits}}{\textit{delay}}$	Warner (1995, 1998)
Kessner (IOM) Index: Simultaneously adjusts for gestation and a) month that prenatal care began, b) number of visits, c) type of obstetric service - whether delivery was by a private obstetric service. Prenatal care classified as *Adequate* (care began in 1st trimester, 9 visits for full-term, and delivery by private obstetric service.) *Intermediate* (either care began after 1st trimester or less than 70% of visits were made) *Inadequate* (care began after 1st trimester and less than 50% visits were made)	Alexander & Kotelchuck (1996)
Modified Kessner (M-IOM) Index: Doesn't take into account whether delivery was by a private obstetric service	Joyce (1994) Alexander & Kotelchuck (1996)
OB-REC: Modifies the Kessner Index by adjusting for the actual number of ACOG recommended visits which is 13 for a full-term pregnancy	Alexander & Kotelchuck (1996)
GINDEX: Modifies the Kessner Index even further by adding 3 additional categories (6 in total) *No care* (woman received no prenatal care) *Missing* (prenatal care data was missing on this individual) *Intensive* (unexpectedly large number of visits - used to indicate high risk pregnancy)	Alexander & Kotelchuck (1996)
APNCU (Adequacy of prenatal care) **Index**: Separate assessments of the a) month that prenatal care began and b) number of visits. Uses an observed-to-recommended ratio combined with onset of care to create index. An additional category: *Adequate plus* (ratio of observed-to-ACOG-recommended number of visits >= 110% - indicates intensive care)	Alexander & Kotelchuck (1996)
PHS (Public Health Service)/**EPPC** (Expert Panel on Prenatal Care) or **PHS-REC**: Alternative schedules emphasizing a) earlier care and b) the number of visits vary by parity - to control for risk. Promotes more comprehensive care and less recommended visits than ACOG for women at low risk.	Alexander & Kotelchuck (1996) Witwer (1990)

Table 4. Summary of public assistance program take-up rates in the literature

Study	Time period	Sample	Public program	Take-up rate
Dubay and Kenney (1997)	1988-1993	Pregnant women	Medicaid	44%
Dubay and Kenney (1997)	1988-1993	Children	Medicaid	69%
Cutler and Gruber (1996)	1988-1993	Children	Medicaid	24%
Blank and Ruggles (1993)	1985-1989	Single mothers	AFDC	62%-72%
Blank and Ruggles (1993)	1985-1989	Single mothers	Food Stamps	54%-66%

Table 5. State outreach efforts

State	Publicity		State	Publicity	
	# of Types of Media Strategies Used	# of Types of Sites Where Information Was Posted		# of Types of Media Strategies Used	# of Types of Sites Where Information Was Posted
Alabama	3	7	Montana	3	6
Alaska	1	6	Nebraska	0	5
Arizona	3	6	Nevada	1	7
Arkansas	4	6	New Hampshire	4	5
California	5	7	New Jersey	5	7
Colorado	5	6	New Mexico	0	3
Connecticut	0	6	New York	6	7
Delaware	0	5	North Carolina	6	7
District of Columbia	5	5	North Dakota	0	5
Florida	3	3	Ohio	4	7
Georgia	3	7	Oklahoma	0	7
Hawaii	6	6	Oregon	0	3
Idaho	5	6	Pennsylvania	0	6
Illinois	5	7	Rhode Island	1	4
Indiana	6	7	South Carolina	0	5
Iowa	3	5	South Dakota	0	7
Kansas	0	0	Tennessee	1	0
Kentucky	4	6	Texas	4	6
Louisiana	0	6	Utah	6	7
Maine	0	0	Vermont	4	4
Maryland	6	6	Virginia	2	4
Massachusetts	4	6	Washington	3	7
Michigan	4	6	West Virginia	0	6
Minnesota	4	7	Wisconsin	6	7
Mississippi	4	6	Wyoming	1	5
Missouri	0	6	**Total: US**	**2.7**	**5.5**

Source: Gold, R.B., Singh, S., & Frost, J. (1993). The Medicaid eligibility expansions for pregnant women: evaluating the strength of state implementation efforts. Family Planning Perspectives, 25(5), 198.

Table 6. Medical Outcome Study: Comparison of measures of well being and functioning among depressed patients, patients with chronic illness and general population †

Measures of well-being and functioning	Physical[a]	Role (physical)[b]	Social[c]	Role (emotional)[b]	Bed Days[d]	Emotional[e]	Energy[f]	Health[g]	Free of Pain[h]
Medical Condition:									
Wells et al. (1989)									
No chronic condition	85.4	87.0	91.7		0.75			73.9	73.4
Depressive disorder	81.3	74.6	83.3		1.12			54.3	63.4
Depressive symptoms	80.1	77.5	84.1		1.23			58.9	63.8
Hays et al. (1995)									
Subthreshold depression	71/71*	57/61	78/76	62/66		65/67	51/52	54/57	68/68
Major depression	73/72	49/50	70/73	41/62		59/65	51/56	56/56	64/61
Dysthymia	64/68	38/35	60/66	64/42		52/54	44/48	50/47	59/58
Double depression	67/75	51/57	56/72	32/46		43/54	38/46	45/55	60/68
Hypertension	80/78	69/72	91/91	81/84		80/81	61/64	64/64	75/77
Congestive heart failure	64/63	53/50	84/84	81/78		83/82	52/51	52/49	71/72
Myocardial infarction	79/82	66/73	91/92	77/84		77/79	59/61	63/64	79/84
Type I diabetes	89/80	86/62	93/88	96/93		88/81	64/75	62/56	74/67
Type II diabetes	77/75	70/66	87/85	83/80		80/78	60/58	59/58	74/75
General population	76	72	81	79		75	59	67	71

† All scores range from 0-100 (where 100 indicates the best functioning and 0 indicates the poorest functioning) except for bed days where a higher number indicates poorer functioning.

[a] *Physical functioning – limitations due to health in activities such as sports, climbing stairs, walking, dressing and bathing*

[b] *Role functioning – extent to which physical or mental health interferes with work, housework or schoolwork.*

[c] *Social functioning – extent to which health interferes with social activities such as visiting friends or relatives*

[d] *Bed days – number of days in bed due to health in past 30 days*

[e] *Emotional well-being – assesses general mood including depressive symptoms, anxiety and positive well-being*

[f] *Energy – assesses perceived energy level*

[g] *Current health – perceptions of current health, such as feeling well or ill*

[h] *Free of pain – extent of bodily pain in the past month*

*The two scores in Hays et al. (i.e. #/#) reflect the longitudinal nature of the data. The first number is the original measurement and the second number is the measurement taken two years later.

Table 7. Epidemiologic Catchment Area (ECA) Study* and National Comorbidity (NC) Study: Incidence of major depression among the population**

Demographic Group	ECA Study	NC Study	
	% of Population with Lifetime Major Depression		
Men (all ages)	10%	12.7%	
Women (all ages)	39%	21.3%	
White	27%	13.5% (male)	22.3%
Black	--	7.2% (male)	15.5%
Hispanic	--	11.7% (male)	23.9%
Non-white	22%	--	
Age 15/18-44	28%	12.9% (male)	21.3%
Age 45-54/59	10%	11.8% (male)	21.8%

*Broadhead, W.E., Blazer, D.G., George, L.K., & Tse, C.K. (1990). Depression, Disability Days, and Days Lost From Work in a Prospective Epidemiologic Survey. Journal of the American Medical Association, 264(19), 2524-2528. **Blazer, D.G., Kessner, R.C., McGonagle, K.A., & Swartz, M.S. (1994). The Prevalence and Distribution of Major Depression in a national Community Sample: The National Comorbidity Survey. American Journal of Psychiatry, 151(7), 979-986.

Table 8. Variable descriptions

	Variable Name	Variable Description
	Live Birth	Whether woman's pregnancy ended in a live birth
Endogenous variables	*Birth weight*	Birth weight of child in grams
	Term birth weight	Sample restricted to full term births (where gestation > 37 weeks) only. This is also a measure of birth weight in grams.
	Low birth weight dummy	Whether infant is born at a birth weight less than 2500 grams.
	Term low birth weight dummy	Sample restricted to full term births (where gestation > 37 weeks) only. Whether infant is born at a birth weight less than 2500 grams.
	Onset	Number of weeks into the pregnancy that prenatal care began
	ACOG adjusted number of visits	Number of actual prenatal care visits made divided by the American College of Obstetricians and Gynecologists (ACOG) number of recommended visits according to gestation.
	Private insurance dummy	Whether woman had private insurance during pregnancy or delivery.
	Medicaid dummy	Whether woman had Medicaid during pregnancy or delivery.
Depression	*CESD average*	Center for Epidemiologic Studies Depression Scale. This variable is an average of this score from the 1988 NMIHS and the 1991 NMIHS follow-up.
Anthropometry	*Mom's birthweight*	Mother's own birth weight in grams
	Mom's height	Mother's own height in inches
	Male dummy	Whether infant is male
Maternal/fertility behaviors	*Smoking*	Number of cigarettes smoked per day during the pregnancy
	Drinking	Number of drinks consumed per week during the pregnancy
	Wanted dummy	Whether woman wanted the pregnancy. The woman was to respond how she felt about the pregnancy before she became pregnant.
	Kidcohab	Number of a woman's own children living in the household
	Parity dummy	Whether woman experienced a previous pregnancy
	Fetal deaths	Number of prior fetal deaths (both abortions and miscarriages) experienced by the woman
	Age	Woman's age at delivery
	Age^2	Age squared
	Age^3	Age cubed
Environmental	*State health care price index (H-index)*	Weighted average of the prices of a hospital room, general medical and dental visits, and a bottle of aspirin. This is an aggregate, state level variable.
	State population density	Population density per square mile. This is an aggregate, state level
	Urban dummy	Whether woman lived in an urban county
Demographics	*Education*	Mother's years of education
	Education^2	Education squared
	Education^3	Education cubed
	Cohab dummy	Whether woman lived with the child's father
	Never married dummy	Whether woman was never married at the time of delivery
	Income	Annual household income in dollars
Measures of ability	*Eligibility88*	Medicaid dollar income eligibility threshold in 1988
	Eligibility97	Medicaid dollar income eligibility threshold in 1997
	State unemployment rate	Percentage of state labor force which are unemployed. This is an aggregate, state level variable.
	Mother & father's occupation and industry	Mother's and father's occupation and industry

Table 9. Descriptive statistics for white and black samples (all births)

		White sample N = 2562		Black sample N = 2106		Diff-in-means
	VARIABLES	**Mean (Std Dev)**	**Min Max**	**Mean (Std Dev)**	**Min Max**	**t-stat**
Endogenous variables	*Birth weight*	3131.42g (872.49g)	413.00g 5783.00g	2953.10 (805.11)	450.00 5520.00	7.25***
	Term birth weight	N/A	N/A	N/A	N/A	N/A
	Low birth weight dummy	0.22 (0.41)	0.00 1.00	0.24 (0.42)	0.00 1.00	-2.00**
	Term low birth weight dummy	N/A	N/A	N/A	N/A	N/A
	Onset	8.57 wks (4.39 wks)	1.00 wks 38.00 wks	10.24 (6.05)	1.00 39.00	10.44***
	ACOG adjusted number of visits	1.08 (0.55)	0.10 7.20	1.03 (0.61)	0.06 7.50	2.50**
	Private insurance dummy	0.72 (0.45)	0.00 1.00	0.36 (0.48)	0.00 1.00	36.00***
	Medicaid dummy	0.13 (0.33)	0.00 1.00	0.46 (0.50)	0.00 1.00	33.00***
Depression	*CESD average*	8.79 (7.43)	0.00 45.39	12.84 (8.52)	0.00 50.00	16.88***
Anthropometric characteristics	*Mom's birthweight*	3177.89g (587.68g)	510.29g 5811.65g	3046.70 (647.29)	425.24 5754.95	7.18***
	Mom's height	64.80" (2.67")	55.00" 79.00"	64.66 (2.89)	53.00 84.00	1.75*
	Male dummy	0.52 (0.50)	0.00 1.00	0.50 (0.50)	0.00 1.00	2.00**
Maternal behavior	*Smoking*	3.41 (7.16)	0.00 40.00	1.66 (4.83)	0.00 60.00	9.72***
	Drinking	0.24 (0.98)	0.00 21.00	0.21 (1.30)	0.00 21.00	1.00
Environmental characteristics	*State health care price index*	102.88 (13.17)	79.94 198.12	101.07 (12.68)	79.94 198.12	4.76***
	State population density	219.35 (435.13)	1.00 9882.60	319.39 (1066.44)	1.00 9882.60	-4.04***
	Urban dummy	0.75 (0.44)	0.00 1.00	0.78 (0.41)	0.00 1.00	-3.00***

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		White sample N = 2562		Black sample N = 2106		Diff-In-means
	VARIABLES	**Mean (Std Dev)**	**Min Max**	**Mean (Std Dev)**	**Min Max**	**t-stat**
Fertility behavior	*Wanted dummy*	0.64 (0.48)	0.00 1.00	0.35 (0.48)	0.00 1.00	29.00***
	Kidcohab	0.79 (0.97)	0.00 7.00	0.93 (1.14)	0.00 7.00	4.67***
	Parity dummy	0.62 (0.48)	0.00 1.00	0.61 (0.49)	0.00 1.00	1.00
	Fetal deaths	0.34 (0.72)	0.00 6.00	0.39 (0.84)	0.00 8.00	-2.50**
	Age	27.02 (5.37)	15.00 44.00	24.24 (5.62)	12.00 44.00	17.38***
	Age^2	759.03 (297.43)	225.00 1936.00	618.96 (291.11)	144.00 1936.00	16.19***
	Age^3	22095.54 (12932.28)	3375.00 85184.00	16622.32 (11961.42)	1728.00 85184.00	15.00***
Demographic characteristics	*Education*	13.40 (2.48)	1.00 20.00	12.53 (2.02)	0.00 20.00	12.43***
	Education^2	185.80 (71.53)	1.00 400.00	161.08 (54.27)	0.00 400.00	13.43***
	Education^3	2665.87 (1625.62)	1.00 8000.00	2126.61 (1156.72)	0.00 8000.00	13.21***
	Cohab dummy	0.90 (0.29)	0.00 1.00	0.47 (0.50)	0.00 1.00	43.00***
	Never married dummy	0.09 (0.28)	0.00 1.00	0.54 (0.50)	0.00 1.0)	45.00***
	Income	$32,479.59 (21,032.23)	$0.00 $76,800.00	$17,368.57 (17,133.18)	0.00 $76,800.00	27.05***
Measures of ability	*Eligibility88*	$8170.56 (3275.84)	$2164.00 $28,805.00	8821.98 (3749.50)	2164.00 $36,056.00	-6.25***
	Eligibility97	$18,431.20 (6804.56)	$10,494.00 $85,960.00	$20,072.87 (8370.14)	$10,494.00 $85,960.00	-7.25***
	State unemployment rate	5.83% (1.67%)	2.40% 12.00%	6.17 (1.96)	2.40 12.00	6.80***
	Mother & father's occupation and industry dummy variables	Descriptive statistics available upon request				

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		White sample N = 2562		Black sample N = 2106		Diff-In-means
	VARIABLES	Mean (Std Dev)	Min Max	Mean (Std Dev)	Min Max	t-stat
Inverse Mills ratios	λ^{LIVE}	1.53 (0.56)	0.00 7.62	1.64 (0.49)	0.00 7.17	5.50
	λ^{PI}	0.00 (0.62)	-3.14 2.54	0.00 (0.65)	-2.86 2.68	0.00
	λ^{MC}	0.00 (0.46)	-1.92 3.28	0.00 (0.69)	-2.11 2.12	0.00
Predicted values	*Predicted value of private insurance*	0.78 (0.42)	0.00 1.00	0.30 (0.46)	0.00 1.00	48.00
	Predicted value of Medicaid	0.09 (0.28)	0.00 1.00	0.48 (0.50)	0.00 1.00	39.00

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level
test-statistic is derived from the following formula:

$$\frac{\bar{x}_{white} - \bar{x}_{black}}{\sqrt{\frac{\sigma^2_{white}}{N_{white}} + \frac{\sigma^2_{black}}{N_{black}}}}$$

Table 10. Descriptive statistics for white and black samples (full-term births)

		White sample N = 2084		Black sample N = 1677		Diff-in-means
	VARIABLES	Mean (Std Dev)	Min Max	Mean (Std Dev)	Min Max	t-stat
Endogenous variables	*Birth weight*	N/A	N/A	N/A	N/A	N/A
	Term birth weight	3434.61 (562.97)	413.00 5783.00	3235.93 (515.78)	1196.00 5520.00	11.27***
	Low birth weight dummy	N/A	N/A	N/A	N/A	N/A
	Term low birth weight dummy	0.07 (0.26)	0.00 1.00	0.09 (0.29)	0.00 1.00	-2.20**
	Onset	8.62 (4.34)	1.00 38.00	10.21 (6.01)	1.00 39.00	-9.35***
	ACOG adjusted number of visits	0.97 (0.34)	0.13 3.33	0.91 (0.41)	0.56 3.55	5.00***
	Private insurance dummy	0.73 (0.45)	0.00 1.00	0.36 (0.48)	0.00 1.00	24.67***
	Medicaid dummy	0.11 (0.31)	0.00 1.00	0.46 (0.50)	0.00 1.00	-25.00***
Depression	*CESD average*	8.41 (7.19)	0.00 45.39	12.65 (8.48)	0.00 50.00	-16.31***
Anthropometric characteristics	*Mom's birthweight*	3201.19 (586.97)	680.38 5811.65	3072.04 (635.11)	425.24 5754.95	6.41***
	Mom's height	64.88 (2.64)	57.00 79.00	64.75 (2.89)	53.00 84.00	1.43
	Male dummy	0.52 (0.50)	0.00 1.00	0.50 (0.50)	0.00 1.00	1.25
Maternal behavior	*Smoking*	3.17 (6.92)	0.00 40.00	1.57 (4.70)	0.00 58.00	8.42***
	Drinking	0.23 (0.93)	0.00 21.00	0.18 (1.09)	0.00 21.00	1.47
Environmental characteristics	*State health care price index*	103.08 (13.38)	79.94 198.12	100.96 (12.66)	79.94 198.12	4.93***
	State population density	218.23 (422.29)	1.00 9882.60	324.56 (1094.32)	1.00 9882.60	-3.76***
	Urban dummy	0.74 (0.44)	0.00 1.00	0.78 (0.41)	0.00 1.00	-2.86***

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		White sample N = 2084		Black sample N = 1677		Diff-in-means
	VARIABLES	**Mean (Std Dev)**	**Min Max**	**Mean (Std Dev)**	**Min Max**	**t-stat**
Fertility behavior	*Wanted dummy*	0.65 (0.48)	0.00 1.00	0.35 (0.48)	0.00 1.00	18.75***
	Kidcohab	0.85 (0.99)	0.00 7.00	0.96 (1.16)	0.00 7.00	-3.06***
	Parity dummy	0.64 (0.48)	0.00 1.00	0.60 (0.49)	0.00 1.00	2.50**
	Fetal deaths	0.31 (0.67)	0.00 5.00	0.36 (0.82)	0.00 8.00	-2.00**
	Age	27.10 (5.28)	15.00 44.00	24.27 (5.56)	12.00 43.00	15.72***
	Age^2	762.11 (293.51)	225.00 1936.00	620.12 (287.21)	144.00 1849.00	14.93***
	Age^3	22,188.57 (12,800.84)	3375.00 85,184.00	16,635.31 (11,745.18)	1728.00 79,507.00	13.84***
Demographic characteristics	*Education*	13.46 (2.46)	6.00 20.00	12.56 (2.04)	0.00 20.00	12.33***
	Education^2	187.34 (71.44)	36.00 400.00	162.01 (55.06)	0.00 400.00	12.30***
	Education^3	2696.53 (1629.03)	216.00 8000.00	2146.51 (1176.60)	0.00 8000.00	12.01***
	Cohab dummy	0.91 (0.28)	0.00 1.00	0.47 (0.50)	0.00 1.00	31.43***
	Never married dummy	0.07 (0.27)	0.00 1.00	0.54 (0.50)	0.00 1.00	-33.57***
	Income	$33,050.29 ($20,935.83)	$0.00 $76,800.00	$17,468.87 ($17,258.14)	$0.00 $76,800	25.02***
Measures of ability	*Eligibility88*	$8284.06 ($3331.86)	$2164.00 $25,179.00	$8885.42 ($3847.62)	$2164.00 $36,056.00	-5.05***
	Eligibility97	$18,667.68 ($6891.45)	$10,494 $85,960	$20,270.97 (8560.52)	$10,494.00 $85,960.00	-6.22***
	State unemployment rate	5.82% (1.65%)	2.40% 12.00%	6.17% 1.95%	3.00% 12.00%	-5.83***
	Mother & father's occupation and industry	Descriptive statistics available upon request				

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		White sample N = 2084		Black sample N = 1677		Diff-in-means
	VARIABLES	**Mean (Std Dev)**	**Min Max**	**Mean (Std Dev)**	**Min Max**	**t-stat**
Inverse Mills ratios	λ^{LIVE}	1.53 (0.56)	0.00 7.62	1.64 (0.50)	0.00 7.17	-6.47***
	λ^{PI}	0.00 (0.62)	-2.94 2.58	0.00 (0.64)	-2.37 2.87	0.00
	λ^{MC}	0.00 (0.45)	-1.79 (3.24)	0.00 (0.69)	-2.21 2.08	0.00
Predicted values	***Predicted value of private insurance***	0.79 (0.41)	0.00 1.00	0.31 (0.46)	0.00 1.00	24.00***
	Predicted value of Medicaid	0.07 (0.25)	0.00 1.00	0.48 (0.50)	0.00 1.00	-31.54***

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level
test-statistic is derived from the following formula:

$$\frac{\bar{x}_{white} - \bar{x}_{black}}{\sqrt{\frac{\sigma^2_{white}}{N_{white}} + \frac{\sigma^2_{black}}{N_{black}}}}$$

Table 11. Key variable means for women that began prenatal care during the 1st trimester and those that began later than the 1st trimester, stratified by race

Variable	Began prenatal care in 1st trimester		Began prenatal care After 1st trimester	
	White (N=2325)	Black (N=1637)	White (N=237)	Black (N=469)
Birth weight (in grams)	3143.51	2961.10	3012.79	2925.19
CES-D score	8.49	12.47	11.70	14.13
Private insurance dummy	0.75	0.39	0.37	0.25
Medicaid dummy	0.10	0.44	0.38	0.55
Age	27.32	24.76	24.06	22.41
Education	13.53	12.68	12.14	12.01
Never married dummy	0.07	0.50	0.29	0.69

Table 12. Center for Epidemiological Studies Depression Scale (CES-D)

The respondent was asked how many times she felt this way during the past week.

Key: *Rarely or none of the time (less than 1 day) = 0*
Some of a little of the time (1-2 days) = 1
Occasionally or a moderate amount of time (3-4 days) = 2
Most or all of the time (5-7 days) = 3

Positive feelings are coded in the opposite way (5-7 days = 0, etc.)

Total score: 0-60 with higher score reflecting more depressed symptoms

Question
I was bothered by things that usually don't bother me.
I had crying spells. I felt lonely.
I felt depressed.
My sleep was restless.
I could not get "going".
I felt lonely.
I felt sad.
I felt fearful.
I felt that everything I did was an effort.
I felt that I could not shake off the blues, even with help from my family or friends.
I talked less than usual.
People were unfriendly.
I did not feel like eating; my appetite was poor.
I had trouble keeping my mind on what I was doing.
I thought my life has been a failure.
I felt that people disliked me.
I enjoyed life.
I felt hopeful about the future.
I was happy
I felt that I was just as good as other people.

Table 13. Key variable means for women who are depressed (CES-D>=16) and women who are not depressed (CES-D<16), stratified by race

Variable	Not depressed (CES-D < 16)		Depressed (CES-D >= 16)	
	White (N=2159)	Black (N=1468)	White (N=403)	Black (N=628)
Birth weight (in grams)	3155.92	2976.18	3000.14	2898.79
Onset	8.38	9.91	9.56	11.01
ACOG adjusted visits	1.07	1.04	1.13	1.02
Private insurance dummy	0.75	0.41	0.55	0.23
Medicaid dummy	0.10	0.42	0.29	0.57
Age	27.45	24.76	24.72	23.00
Education	13.61	12.78	12.32	11.95
Never married dummy	0.07	0.50	0.16	0.64

Table 14. Key variable means for women with low birth weight infants (<2500 grams) and normal birth weight infants (2500-6000 grams), stratified by race

Variable	Low birth weight (< 2500 grams/5.51 lbs)		Normal birth weight (2500 – 6000 grams)	
	White (N=564)	Black (N=1611)	White (N=1998)	Black (N=1611)
CES-D score	10.02	13.61	8.44	12.60
Onset	8.52	10.48	8.58	10.16
ACOG adjusted visits	1.44	1.32	0.98	0.94
Private insurance dummy	0.66	0.34	0.73	0.36
Medicaid dummy	0.19	0.49	0.11	0.46
Age	26.87	24.14	27.07	24.26
Education	13.04	12.33	13.51	12.59
Never married dummy	0.12	0.59	0.08	0.53

Table 15. Results from insurance and Medicaid equations (all births)

		White sample		Black sample	
	VARIABLES	**Private insurance N=2562**	**Medicaid N=2562**	**Private insurance N=2106**	**Medicaid N=2106**
	Intercept	-1.95 (-0.60)	-7.67 (-1.74)*	3.59 (0.87)	-2.76 (-0.67)
Measures of ability	*Eligibility88*	-0.00002 (-1.55)	0.00005 (3.22)***	-0.00003 (-2.09)**	0.00005 (4.22)****
	State unemployment rate	-0.05 (-2.42)**	-0.04 (-1.62)	0.01 (0.52)	-0.07 (-3.95)***
	Mother & father's Occupation and industry	Results available upon request			
Environmental characteristics	*State health care price index*	-0.007 (-2.45)**	0.004 (1.24)	-0.0002 (-0.07)	-0.003 (-0.80)
	State population density	0.0003 (2.71)***	-0.0002 (-1.87)*	0.00004 (0.13)	0.00005 (1.60)
	Urban dummy	0.10 (1.32)	-0.06 (-0.60)	0.005 (0.05)	-0.14 (-1.60)
Depression	*CESD average*	-0.001 (-0.23)	0.02 (3.54)***	-0.01 (-2.23)**	0.009 (2.25)**
Anthropometric characteristics	*Mom's birthweight*	0.00003 (0.61)	0.00002 (0.24)	-0.0001 (-1.93)*	0.00006 (1.27)
	Mom's height	-0.24 (-0.18)	-0.04 (-2.06)**	-0.007 (-0.60)	0.01 (0.90)
	Male dummy	0.03 (0.50)	0.08 (0.95)	-0.10 (-1.46)	-0.03 (-0.45)
Maternal behavior	*Smoking*	-0.01 (-2.71)***	0.007 (1.34)	-0.03 (-3.65)***	0.02 (2.79)***
	Drinking	-0.01 (-0.52)	0.06 (2.04)**	0.01 (0.36)	-0.001 (-0.06)
Fertility behavior	*Wanted dummy*	0.20 (2.60)***	-0.32 (-3.19)***	0.05 (0.62)	-0.03 (-0.36)
	Kidcohab	-0.09 (-1.81)*	-0.04 (-0.67)	-0.09 (-1.96)**	0.10 (2.18)**
	Parity dummy	-0.88 (-0.11)	0.07 (0.63)	-0.002 (-0.02)	0.15 (1.91)*
	Fetal deaths	-0.002 (-0.04)	0.14 (2.45)**	0.04 (1.03)	-0.03 (0.79)

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		White sample		Black sample	
	VARIABLES	**Private insurance N=2562**	**Medicaid N=2562**	**Private insurance N=2106**	**Medicaid N=2106**
Fertility behavior cont.	*Age*	-0.14 (-0.43)	0.93 (2.32)**	-0.86 (-3.28)***	1.13 (4.52)***
	Age^2	0.01 (0.86)	-0.35 (-2.38)**	0.03 (3.22)***	-0.04 (-4.53)***
	Age^3	-0.0002 (0.25)	0.0004 (2.32)**	-0.0004 (-3.03)***	0.0005 (4.41)***
Demographic characteristics	*Education*	0.04 (0.13)	0.92 (1.28)	0.45 (0.59)	-1.31 (-1.65)
	Education^2	0.02 (0.87)	-0.09 (-1.60)	-0.01 (-0.25)	0.09 (1.44)
	Education^3	-0.0008 (-1.47)	0.002 (1.73)*	-0.00004 (-0.03)	-0.002 (-1.29)
	Cohab dummy	0.54 (4.44)***	-0.64 (-5.03)***	0.34 (4.37)***	-0.40 (-5.13)***
	Income	0.00002 (7.55)***	-0.00003 (-6.53)***	0.00002 (9.35)***	-0.00003 (-8.96)***
Mills ratio	λ^{LIVE}	-0.005 (-0.09)	-0.03 (-0.38)	0.09 (0.99)	-0.11 (-1.34)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 16. Results from prenatal care equations (all births)

		White sample		Black sample	
	VARIABLES	**Onset N=2562**	**ACOG rec # of visits N=2562**	**Onset N=2106**	**ACOG rec # of visits N=2106**
	Intercept	28.17 (2.81)***	-1.48 (-1.56)	25.17 (2.52)**	1.03 (1.15)
Environmental characteristics	***State health care price index***	-0.007 (-0.95)	-0.0003 (-0.35)	-0.004 (-0.40)	0.001 (0.76)
	State population density	-0.0003 (-2.10)**	0.000006 (0.22)	0.00003 (0.24)	0.000007 (0.54)
	Urban dummy	-0.36 (-1.64)*	-0.001 (-0.04)	-0.36 (-1.05)	0.03 (0.98)
Endogenous variables	***Private insurance dummy***	-1.62 (-2.07)**	0.14 (1.78)*	-2.00 (-1.68)*	0.16 (0.14)
	Medicaid dummy	-0.29 (-0.30)	0.22 (2.41)**	-1.20 (-0.91)	0.05 (0.37)
Depression	***CESD average***	0.007 (0.54)	0.005 (2.45)**	0.02 (0.97)	0.002 (0.92)
Anthropometric characteristics	***Mom's birthweight***	0.0006 (0.44)	-0.00004 (-2.23)**	0.0003 (1.47)	-0.00003 (-1.15)
	Mom's height	-0.04 (-1.28)	0.003 (0.62)	0.01 (0.32)	0.001 (0.29)
	Male dummy	0.22 (1.34)	-0.003 (-0.13)	-0.58 (-0.22)	-0.03 (-1.01)
Maternal behavior	***Smoking***	0.001 (0.07)	-0.001 (-0.56)	0.0003 (0.01)	-0.001 (-0.48)
	Drinking	0.18 (1.47)	-0.02 (-2.98)***	0.20 (1.66)*	-0.004 (-0.34)
Fertility behavior	***Wanted dummy***	-1.10 (-5.00)***	-0.01 (-0.37)	-1.66 (-5.87)***	0.05 (1.59)
	Kidcohab	0.40 (2.84)***	-0.09 (-6.63)***	-0.02 (-0.13)	-0.05 (-2.71)***
	Parity dummy	-0.08 (-0.38)	0.06 (2.06)**	-0.04 (-0.11)	0.04 (1.19)
	Fetal deaths	-0.09 (-0.74)	0.03 (1.96)**	-0.08 (-0.53)	0.05 (2.70)***
	Age	-1.80 (-1.82)*	0.20 (2.25)**	-0.90 (-0.92)	-0.11 (-1.25)

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		White sample		Black sample	
	VARIABLES	**Onset N=2562**	**ACOG rec # of visits N=2562**	**Onset N=2106**	**ACOG rec # of visits N=2106**
Fertility beh. Cont.	*Age²*	0.06 (1.60)	-0.007 (-2.10)**	0.02 (0.56)	0.004 (1.27)
	Age³	-0.006 (-1.38)	0.00008 (2.03)**	-0.0001 (-0.26)	-0.00005 (-1.24)
Demographic characteristics	*Education*	0.92 (1.48)	0.08 (1.08)	-0.99 (-1.05)	0.11 (1.45)
	Education²	-0.06 (-1.38)	-0.005 (-0.81)	0.11 (1.51)	-0.006 (-0.89)
	Education³	0.001 (1.26)	0.0001 (0.64)	-0.004 (-1.95)*	0.0001 (0.58)
	Cohab dummy	-0.38 (-0.80)	0.04 (0.78)	-0.99 (-2.61)**	0.04 (1.04)
	Income	-0.000007 (-1.23)	-0.000001 (-1.78)*	-0.000005 (-0.40)	0.0000004 (0.33)
Inverse Mills ratios	λ^{LIVE}	-0.09 (-0.57)	-0.02 (-1.21)	-0.33 (-1.15)	0.04 (1.42)
	λ^{PI}	0.67 (1.52)	-0.05 (-1.08)	1.13 (1.61)	0.006 (0.09)
	λ^{MC}	0.82 (1.49)	-0.07 (-1.31)	0.61 (0.78)	-0.01 (-0.18)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 17. Results from different specifications of birth weight (prenatal care=onset)

		White sample		Black sample	
	VARIABLES	**Birth weight N=2562**	**Term birth weight N=2084**	**Birth weight N=2106**	**Term birth weight N=1677**
	Intercept	409.95 (0.20)	395.83 (0.24)	-180.81 (-0.09)	1004.30 (.91)
Endogenous variables	*Onset*	-16.76 (-0.28)	21.25 (0.61)	-11.49 (-0.26)	2.46 (0.10)
	ACOG adjusted number of visits	—	—	—	—
	Private insurance dummy	-123.84 (-0.70)	27.64 (0.26)	-111.67 (-0.60)	-125.88 (-1.07)
	Medicaid dummy	-314.43 (-2.25)**	-52.78 (-0.47)	-115.97 (-0.68)	-268.01 (-2.34)**
Depression	*CESD average*	-2.91 (-1.22)	0.21 (0.12)	-3.64 (-1.66)*	-2.55 (-1.66)*
Anthropometric characteristics	*Mom's birthweight*	0.24 (7.85)***	0.19 (8.52)***	0.13 (4.04)***	0.14 (6.06)***
	Mom's height	29.39 (4.50)***	31.64 (6.93)***	31.72 (5.30)***	23.11 (5.42)***
	Male dummy	150.35 (4.27)***	135.04 (5.35)***	86.30 (2.48)**	100.28 (4.10)***
Maternal behavior	*Smoking*	-16.38 (-6.27)***	-16.04 (-7.69)***	-14.92 (-3.91)***	-12.75 (-4.63)***
	Drinking	1.59 (0.08)	3.12 (0.29)	-19.91 (-1.34)	-21.51 (-1.83)*
Fertility behavior	*Wanted dummy*	7.65 (0.10)	21.30 (0.50)	-44.84 (-0.51)	15.11 (0.30)
	Kidcohab	177.10 (5.59)***	53.75 (2.51)**	55.18 (2.82)***	22.10 (1.62)
	Parity dummy	60.12 (1.45)	86.04 (2.87)***	-19.90 (-1.34)	53.84 (1.80)*
	Fetal deaths	-51.62 (-1.86)*	29.49 (1.70)*	-75.94 (-2.71)***	-1.57 (-0.09)
	Age	74.25 (0.40)	34.54 (0.27)	104.69 (0.70)	72.12 (0.78)
	Age^2	-3.20 (-0.50)	-1.25 (-0.28)	-3.10 (-0.57)	-2.58 (-0.74)
	Age^3	0.04 (0.49)	0.01 (0.22)	0.03 (0.42)	0.03 (0.70)

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		White sample		Black sample	
	VARIABLES	**Birth weight N=2562**	**Term birth weight N=2084**	**Birth weight N=2106**	**Term birth weight N=1677**
Demographic characteristics	*Education*	-86.55 (-0.63)	-107.03 (-0.49)	-7.71 (-0.04)	-66.51 (-0.91)
	Education^2	8.40 (0.79)	11.55 (0.75)	-0.51 (-0.04)	5.22 (0.79)
	Education^3	-0.21 (-0.79)	-0.32 (-0.91)	0.06 (0.15)	-0.11 (-0.60)
	Never married dummy	22.00 (0.22)	-11.54 (-0.19)	-11.08 (-0.22)	7.63 (0.22)
Inverse Mills ratios	λ^{LIVE}	-32.61 (-0.94)	-26.24 (-1.30)	-34.72 (-0.90)	-7.20 (-0.27)
	λ^{PI}	38.29 (0.43)	-10.91 (-0.19)	68.28 (0.62)	65.92 (0.93)
	λ^{MC}	102.85 (1.12)	-13.18 (-0.22)	49.69 (0.47)	140.09 (2.03)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 18. Results from different specifications of birth weight (pnc=acogadj)

		White sample		Black sample	
	VARIABLES	**Birth Weight N=2562**	**Term birth weight N=2084**	**Birth weight N=2106**	**Term birth weight N=1677**
	Intercept	446.12 (0.22)	2129.40 (1.244)	-910.27 (-0.51)	1488.00 (1.20)
Endogenous variables	*Onset*	---	---	---	---
	ACOG adjusted number of visits	259.66 (0.33)	1084.80 (1.22)	366.38 (0.53)	-304.94 (-0.53)
	Private insurance dummy	-107.84 (-0.76)	-98.58 (-0.81)	-102.24 (-0.57)	-148.51 (-1.36)
	Medicaid dummy	-372.10 (-1.55)	-133.02 (-0.83)	-112.75 (-0.60)	-294.69 (-2.31)**
Depression	*CESD average*	-4.29 (-0.93)	-2.23 (-0.77)	-4.38 (-1.69)*	-2.52 (-1.68)*
Anthropometric characteristics	*Mom's birthweight*	0.25 (5.43)***	0.20 (7.47)***	0.13 (3.75)***	0.14 (6.57)***
	Mom's height	29.24 (4.05)***	31.76 (5.83)***	31.11 (3.75)***	23.12 (5.30)***
	Male dummy	147.09 (4.21)***	129.27 (4.34)***	97.07 (2.27)**	95.62 (3.54)***
Maternal behavior	*Smoking*	-16.06 (-5.47)***	-15.70 (-6.11)***	-14.46 (-3.46)***	-13.41 (-4.24)***
	Drinking	4.87 (0.19)	19.15 (1.26)	-20.65 (-1.50)	-25.43 (-1.77)*
Fertility behavior	*Wanted dummy*	27.20 (0.63)	-9.99 (-0.27)	-43.41 (-0.80)	25.88 (0.64)
	Kidcohab	192.89 (2.72)***	113.01 (2.50)**	72.29 (2.01)**	17.85 (1.16)
	Parity dummy	45.98 (0.70)	26.60 (0.45)	-35.40 (-0.61)	57.75 (1.80)*
	Fetal deaths	-58.67 (-1.54)	13.98 (0.56)	-93.79 (-1.99)**	7.92 (0.30)
	Age	44.29 (0.19)	-109.83 (-0.72)	157.54 (0.95)	28.69 (0.24)
	Age^2	-2.09 (-0.25)	3.56 (0.64)	-4.99 (-0.79)	-0.93 (-0.20)
	Age^3	0.02 (0.22)	-0.04 (-0.63)	0.05 (0.63)	0.01 (0.17)

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		White sample		Black sample	
	VARIABLES	**Birth Weight N=2562**	**Term birth weight N=2084**	**Birth weight N=2106**	**Term birth weight N=1677**
Demographic characteristics	*Education*	-129.23 (-0.90)	-341.32 (-1.08)	-35.34 (-0.17)	-33.94 (-0.37)
	Education^2	11.05 (1.02)	27.46 (1.25)	0.35 (0.02)	3.47 (0.52)
	Education^3	-0.26 (-0.96)	-0.67 (-1.34)	0.06 (0.15)	-0.08 (-0.47)
	Cohab dummy	—	—	—	—
	Never married dummy	23.42 (0.24)	15.90 (0.22)	3.97 (0.07)	-4.46 (-0.11)
Inverse Mills ratios	λ^{LIVE}	-26.32 (-0.67)	-16.68 (-0.62)	-43.59 (-0.92)	-5.55 (-0.20)
	λ^{PI}	25.49 (0.36)	37.16 (0.59)	57.24 (0.54)	77.35 (1.19)
	λ^{MC}	110.25 (1.01)	42.50 (0.45)	43.75 (0.38)	155.19 (2.02)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 19. Results from the instrumental variables (IV) approach

		White sample		Black sample	
		Birth weight (N=2562)		Birthweight (N=2106)	
	VARIABLES	With onset	With ACOG	With onset	With ACOG
	Intercept	893.00 (0.53)	-1548.70 (-0.94)	-277.09 (-0.16)	-793.31 (-0.45)
Endogenous variables	*Onset*	-40.51 (-1.33)	--	-5.58 (-0.16)	--
	ACOG adjusted number of visits	--	-856.26 (-1.92)*	--	306.52 (0.50)
Insurance	*Private insurance predicted value*	-24.33 (-0.40)	-0.03 (-0.001)	5.41 (0.09)	0.25 (0.004)
	Medicaid predicted value	-90.04 (-1.13)	-26.76 (-0.31)	18.75 (0.35)	12.60 (0.22)
Depression	*CESD average*	-3.31 (-1.39)	0.71 (0.22)	-3.78 (-1.75)*	-4.33 (-1.80)*
Anthropometric characteristics	*Mom's birthweight*	0.24 (7.81)***	0.20 (5.80)***	0.12 (4.07)***	0.13 (3.80)***
	Mom's height	29.56 (4.56)***	32.62 (5.29)***	31.56 (5.29)***	31.14 (4.83)***
	Male dummy	151.83 (4.48)***	142.68 (4.61)***	91.11 (2.66)***	99.60 (2.43)**
Maternal behavior	*Smoking*	-16.46 (-6.28)***	-17.63 (-6.89)***	-14.96 (-3.95)***	-14.58 (-3.56)***
	Drinking	3.67 (0.19)	-21.74 (-1.14)	-21.27 (-1.54)	-21.04 (-1.56)
Fertility behavior	*Wanted dummy*	-13.31 (-0.26)	25.25 (0.64)	-32.52 (-0.44)	-38.52 (-0.74)
	Kidcohab	188.77 (7.32)***	95.18 (2.21)**	53.07 (2.92)***	67.29 (1.98)**
	Parity dummy	57.33 (1.34)	112.83 (2.37)**	-25.93 (-0.61)	-38.86 (-0.72)
	Fetal deaths	-56.98 (-2.06)**	-22.70 (-0.75)	-75.74 (-2.73)***	-91.01 (-2.09)**
	Age	21.53 (0.13)	290.24 (1.57)	89.25 (0.64)	130.56 (0.82)
	Age^2	-1.59 (-0.27)	-10.37 (-1.59)	-2.42 (-0.47)	-3.95 (-0.65)

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		White sample		Black sample	
		Birthweight (N=2562)		Birthweight (N=2106)	
	VARIABLES	With onset	With ACOG	With onset	With ACOG
	Age[3]	0.02 (0.29)	0.12 (1.52)	-2.42 (-0.47)	0.04 (0.48)
Demographic characteristics	*Education*	-54.09 (-0.44)	-21.45 (-0.18)	4.03 (0.02)	-23.35 (-0.12)
	Education[2]	6.38 (0.65)	5.01 (0.56)	-1.25 (-0.09)	-0.09 (-0.006)
	Education[3]	-0.17 (-0.67)	-0.15 (-0.67)	0.07 (0.20)	0.06 (0.16)
	Cohab dummy	--	--	--	--
	Never married dummy	36.68 (0.42)	-83.29 (-1.01)	-25.39 (-0.54)	-10.664 (-0.18)
Mills ratio	λ^{LIVE}	-29.56 (-0.84)	-46.86 (-1.35)	-31.97 (-0.84)	-40.48 (-0.89)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 20. Results from treating all variables as exogenous

		White sample		Black sample	
		Birthweight (N=2562)		Birthweight (N=2106)	
	VARIABLES	With onset	With ACOG	With onset	With ACOG
	Intercept	-318.69 (-0.22)	-1037.20 (-0.76)	-529.70 (-0.36)	4.06 (0.003)
Endogenous variables	*Onset*	7.62 (2.09)**	--	0.96 (0.35)	--
	ACOG adjusted number of visits	--	-559.61 (-15.87)***	--	-402.55 (-13.76)***
Insurance	*Private insurance*	-42.43 (-0.96)	-17.50 (-0.42)	0.84 (0.12)	13.67 (0.27)
	Medicaid dummy	-185.55 (-2.81)**	-111.54 (-1.79)*	-34.32 (-0.71)	-26.18 (-0.56)
Depression	*CESD average*	-3.61 (-1.57)	-0.65 (-0.29)	-3.74 (-1.82)*	-3.14 (-1.56)
Anthropometric characteristics	*Mom's birthweight*	0.24 (7.95)***	0.21 (7.51)***	0.12 (4.37)***	0.11 (4.21)***
	Mom's height	30.65 (4.92)***	31.78 (5.48)***	31.59 (5.34)***	32.08 (5.68)***
	Male dummy	142.21 (4.40)***	143.62 (4.77)***	90.57 (2.66)***	79.44 (2.46)**
Maternal behavior	*Smoking*	-16.67 (-6.62)***	-17.17 (-7.17)***	-14.71 (-3.94)***	-15.25 (-4.06)***
	Drinking	-3.45 (-0.20)	-14.67 (-0.89)	-22.66 (-1.84)*	-24.21 (-1.88)*
Fertility behavior	*Wanted dummy*	39.45 (0.01)	24.64 (0.67)	-22.81 (-0.59)	-3.60 (-0.10)
	Kidcohab	166.33 (8.14)***	121.41 (6.39)***	56.48 (3.19)***	38.15 (2.28)**
	Parity dummy	60.89 (1.48)	94.93 (2.50)**	-22.30 (-0.53)	-4.30 (-0.11)
	Fetal deaths	-51.07 (-1.89)*	-32.31 (-1.27)	-75.21 (-2.73)***	-54.47 (-2.10)**
	Age	112.99 (0.75)	226.15 (1.57)	112.10 (0.83)	63.29 (0.49)
	Age^2	-4.31 (-0.78)	-8.24 (-1.58)	-3.23 (-0.63)	-1.34 (-0.28)

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		White sample		Black sample	
		Birthweight (N=2562)		Birthweight (N=2106)	
	VARIABLES	With onset	With ACOG	With onset	With ACOG
	Age^3	0.05 (0.70)	0.09 (1.48)	0.03 (0.43)	0.005 (0.08)
Demographic characteristics	*Education*	-106.20 (-0.91)	-47.70 (-0.44)	11.14 (0.07)	52.52 (0.34)
	Education^2	10.14 (1.10)	6.39 (0.75)	-2.42 (-0.18)	-4.61 (-0.39)
	Education^3	-0.25 (-1.07)	-0.17 (-0.81)	0.12 (0.35)	0.16 (0.52)
	Cohab dummy	--	--	--	--
	Never married dummy	-31.86 (-0.46)	-56.59 (-0.81)	-12.82 (-0.30)	-32.86 (-0.80)
Mills ratio	λ^{LIVE}	-28.44 (-0.83)	-41.63 (-1.27)	--	--

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 21. Results from the reduced-form birth weight equation (all births)

		White sample	Black sample
	VARIABLES	**Birth weight**	**Birth weight**
	Intercept	-323.37 (-0.22)	-414.59 (-0.27)
Measures of ability	*Eligibility88*	0.006 (0.99)	0.0007 (0.12)
	State unemployment rate	0.92 (0.09)	-21.75 (2.11)**
	Mother & father's Occupation and industry dummy variables	Results available upon request	
Environmental characteristics	*State health care price index*	1.94 (1.48)	-2.79 (-1.43)
	State population density	-0.05 (-1.09)	-0.002 (-0.11)
	Urban dummy	-13.66 (-0.35)	19.32 (0.41)
Depression	*CESD average*	-3.70 (-1.61)	-3.58 (-1.76)*
Anthropometric characteristics	*Mom's birthweight*	0.23 (7.81)***	0.13 (4.54)***
	Mom's height	30.89 (4.90)***	30.98 (5.26)***
	Male dummy	149.92 (4.60)***	90.87 (2.68)***
Maternal behavior	*Smoking*	-16.64 (-6.64)***	-15.75 (-4.24)***
	Drinking	-0.51 (-0.03)	-20.78 (-1.69)*
Fertility behavior	*Wanted dummy*	40.66 (1.11)	-15.04 (-0.39)
	Kidcohab	155.14 (6.57)***	53.68 (2.64)***
	Parity dummy	57.11 (1.38)	-26.29 (-0.64)
	Fetal deaths	-51.48 (-1.93)*	-80.99 (-2.98)***

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		White sample	Black sample
	VARIABLES	**Birth weight**	**Birth weight**
Fertility behavior cont.	*Age*	67.45 (0.44)	146.11 (1.07)
	Age^2	-2.90 (-0.52)	-4.36 (-0.85)
	Age^3	0.03 (0.48)	0.04 (0.62)
Demographic characteristics	*Education*	-96.83 (-0.82)	11.80 (0.65)
	Education^2	9.89 (-0.82)	-1.33 (-0.10)
	Education^3	-0.26 (-1.07)	0.05 (0.15)
	Cohab dummy	144.01 (2.09)**	0.69 (0.02)
	Income	-0.000002 (-0.002)	0.001 (0.87)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 22. Results from low birth weight models (prenatal care=onset)

		White sample		Black sample	
	VARIABLES	**Low birth weight N=2562**	**Term low birth weight N=2084**	**Low birth Weight N=2106**	**Term low birth weight N=1677**
Endogenous variables	*Intercept*	-0.90 (-0.24)	-0.39 (-0.07)	1.68 (0.45)	3.39 (0.80)
	Onset	0.08 (0.72)	-0.08 (-0.60)	0.07 (0.79)	0.04 (0.45)
	ACOG adjusted number of visits	—	—	—	—
	Private insurance dummy	0.18 (0.55)	-0.29 (-0.74)	0.09 (0.25)	0.03 (0.07)
	Medicaid dummy	0.67 (2.53)**	0.54 (1.33)	0.08 (0.24)	0.37 (0.84)
Depression	*CESD average*	0.003 (0.68)	-0.002 (-0.31)	0.003 (0.74)	0.001 (0.17)
Anthropometric characteristics	*Mom's birthweight*	-0.0003 (-5.57)***	-.0004 (-4.71)***	-0.0002 (-2.93)***	-0.0003 (-3.10)
	Mom's height	-0.02 (-1.62)	-0.03 (-1.57)	-0.04 (-3.78)***	-0.05 (-3.20)***
	Male dummy	-0.14 (-2.19)**	-0.26 (-2.62)***	-0.06 (-0.92)	-0.15 (-1.71)*
Maternal behavior	*Smoking*	0.02 (5.30)***	0.03 (5.84)***	0.02 (2.35)**	0.02 (2.29)**
	Drinking	0.005 (0.13)	-0.01 (-0.30)	0.03 (0.98)	0.03 (0.73)
Fertility behavior	*Wanted dummy*	0.02 (0.14)	-0.100 (-0.65)	0.13 (0.80)	-0.06 (-0.33)
	Kidcohab	-0.28 (-4.35)***	-0.07 (-0.84)	-0.12 (-2.87)***	-0.12 (-2.20)**
	Parity dummy	-0.15 (-1.91)*	-0.28 (-2.35)**	0.07 (0.85)	-0.13 (-1.14)
	Fetal deaths	0.10 (2.30)**	-0.10 (-1.39)	0.09 (2.22)**	-0.03 (-0.51)
	Age	-0.03 (-0.10)	-0.10 (-0.21)	-0.08 (-0.29)	-0.38 (-1.10)
	Age^2	0.003 (0.27)	0.004 (0.21)	0.002 (0.25)	0.02 (1.21)
	Age^3	-0.00004 (-0.32)	-0.00003 (-0.14)	-0.00002 (-0.14)	-0.0002 (-1.22)

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		White sample		Black sample	
	VARIABLES	**Low birth weight N=2562**	**Term low birth weight N=2084**	**Low birth Weight N=2106**	**Term low birth weight N=1677**
Demographic characteristics	***Education***	0.29 (0.89)	0.88 (1.22)	0.09 (0.21)	0.33 (0.88)
	Education^2	-0.02 (-0.91)	-0.07 (-1.26)	-0.004 (-0.12)	-0.02 (-0.72)
	Education^3	0.0005 (0.84)	0.16 (1.23)	-0.000009 (-0.01)	0.0004 (0.47)
	Never married dummy	-0.18 (0.14)	-0.18 (-0.09)	0.06 (0.66)	0.08 (0.67)
Inverse Mills ratios	λ^{LIVE}	0.03 (0.41)	0.02 (0.25)	0.06 (0.85)	0.02 (0.16)
	λ^{PI}	-0.02 (0.11)	0.14 (0.66)	-0.04 (-0.18))	0.05 (0.19)
	λ^{MC}	-0.34 (-2.02)**	-0.26 (-1.16)	-0.02 (-0.12)	-0.11 (-0.39)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 23. Results from low birth weight models (prenatal care=acogadj)

		White sample		Black sample	
	VARIABLES	**Birth Weight N=2562**	**Term birth weight N=2084**	**Birth Weight N=2106**	**Term birth weight N=1677**
Endogenous variables	*Intercept*	-0.60 (-0.15)	-7.97 (-1.28)	4.46 (1.31)	4.71 (1.08)
	Onset	—	—	—	—
	ACOG adjusted number of visits	-0.91 (-0.57)	-5.19 (-1.35)	-0.88 (-0.66)	-0.21 (-0.11)
	Private insurance dummy	0.08 (0.30)	0.31 (0.59)	-0.03 (-0.08)	-0.08 (-0.19)
	Medicaid dummy	0.86 (1.79)*	0.95 (1.37)	0.07 (0.20)	0.31 (0.66)
Depression	*CESD average*	.008 (0.85)	0.009 (0.74)	0.005 (1.11)	0.002 (0.32)
Anthropometric characteristics	*Mom's birthweight*	-0.0003 (-3.77)***	-0.0004 (-3.89)***	-0.0002 (-2.58)***	-0.0002 (-3.21)***
	Mom's height	-0.02 (-1.36)	-0.03 (-1.11)	-0.04 (-3.18)***	-0.05 (-3.12)***
	Male dummy	-0.12 (-1.80)*	-0.22 (-1.64)*	-0.09 (-1.07)	-0.15 (-1.61)
Maternal behavior	*Smoking*	0.02 (4.03)***	0.03 (3.56)***	0.01 (1.97)**	0.02 (1.91)*
	Drinking	-0.003 (-0.06)	-0.09 (-1.48)	0.04 (1.26)	0.03 (0.77)
Fertility behavior	*Wanted dummy*	-0.07 (-0.83)	0.03 (0.16)	0.06 (0.58)	-0.13 (-0.87)
	Kidcohab	-0.33 (-2.24)**	-0.34 (-1.60)	-0.16 (-2.65)***	-0.13 (-2.22)**
	Parity dummy	-0.11 (-0.78)	-0.006 (-0.02)	0.10 (0.88)	-0.13 (-1.15)
	Fetal deaths	0.12 (1.75)*	-0.02 (-0.24)	0.13 (1.58)	-0.02 (-0.24)
	Age	0.04 (0.10)	0.56 (0.89)	-0.25 (-0.83)	-0.45 (-1.07)
	Age^2	-0.00003 (-0.002)	-0.02 (0.82)	0.008 (0.72)	0.02 (1.13)
	Age^3	-0.0000004 (-0.002)	0.0002 (0.82)	-0.00008 (-0.55)	-0.0002 (-1.11)

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		White sample		Black sample	
	VARIABLES	**Birth Weight N=2562**	**Term birth weight N=2084**	**Birth Weight N=2106**	**Term birth weight N=1677**
Demographic characteristics	***Education***	0.46 (1.34)	2.01 (1.44)	0.12 (0.27)	0.30 (0.71)
	***Education*^{2}**	-0.03 (-1.28)	-0.14 (-1.45)	-0.001 (-0.04)	-0.02 (-0.57)
	***Education*^{3}**	0.0007 (1.14)	0.003 (1.43)	-0.0002 (-0.22)	0.0002 (0.30)
	Never married dummy	-0.17 (-0.89)	-0.12 (-0.37)	0.02 (0.21)	0.08 (0.56)
Inverse Mills ratios	λ^{LIVE}	0.004 (0.05)	-0.02 (-0.18)	0.07 (0.84)	0.02 (0.16)
	λ^{PI}	0.05 (0.33)	-0.09 (-0.34)	0.04 (0.20)	0.11 (0.46)
	λ^{MC}	-0.35 (-1.63)	-0.52 (-1.21)	-0.02 (-0.07)	-0.07 (-0.25)

*denotes significance at the 10% level
**denotes significance at the 5% level
***denotes significance at the 1% level

Table 24. Major state-level Medicaid eligibility expansions since the mid-1980's

State	Income Eligibility Levels as a Function of % of FPL			
	December 1986†	April 1987 - January 1989	January 1992†	October 1997
AL	15.5%	100%	133%	133%
AK	77.9%	100%	133%	133%
AZ	36.3%*	100%	140%	140%
AR	34.0%	100%	185%	133% [200%] ***
CA	108.6%	*	185%**	200%
CO	55.4%	*	133%	133%
CT	80.0%	185%	185%	185%
DE	40.8%	100%	160%	185%
DC	63.8%	100%	185%	Not reported
FL	44.8%	100%	150%	185%
GA	45.0%	100%	133%	185%
HI	54.3%	100%	185%**	300%††
ID	40.0%	67%	133%	133%
IL	60.3%	100%	133%	133%
IN	33.7%	50%	150%	150%
IA	66.8%	150%	185%	185%
KS	60.5%	100%	150%	150%
KY	35.1%	125%	185%	185%
LA	33.9%	100%	133%	133%
ME	69.0%	185%	185%	185%
MD	53.8%	100%	185%	185%†††
MA	86.5%	185%	185%**	185%
MI	68.5%	185%	185%	185%
MN	70.0%	185%	185%	275%†††
MS	48.4%	185%	185%	185%
MO	36.7%	100%	133%	185%
MT	53.2%	*	133%	133%
NE	59.2%	100%	133%	150%
NV	37.5%	*	133%	133%
NH	61.4%	*	133%	185%
NJ	71.2%	100%	185%	185%
NM	33.9%	100%	185%	185%
NY	80.0%	*	185%	185%
NC	43.8%	100%	185%	185%
ND	57.2%	*	133%	133%
OH	39.7%	100%	133%	133%
OK	54.8%	100%	133%	150%
OR	69.6%	100%	133%	133%
PA	55.9%	100%	133%	185%
RI	83.3%	185%	185%**	250%†††

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State	Income Eligibility Levels as a Function of % of FPL			
	December 1986†	April 1987 - January 1989	January 1992†	October 1997
AL	15.5%	100%	133%	133%
SC	50.0%	100%	185%	185%
SD	48.2%	100%	133%	133%
TN	27.3%	100%	185%	400%†††
TX	35.1%	100%	185%	185%
UT	65.9%	100%	133%	133%
VT	80.0%	185%	185%**	200% [225%]***
VA	47.1%	100%	133%	133%
WA	72.6%	90%	185%	189% [200%]***
WV	38.1%	150%	150%	150%
WI	84.3%	*	155%	185%
WY	47.4%	100%	133%	133%

Sources: **Columns 1 and 3** - Gold, R.B., Singh, S., & Frost, J. (1993). The Medicaid eligibility expansions for pregnant women: evaluating the strength of state implementation efforts. Family Planning Perspectives, 25(5), 198. **Column 2** - Torres, A. & Kenney,A.M. (1989). Expanding Medicaid coverage for pregnant women: Estimates of the impact and cost. Family Planning Perspectives, 21(1), 20. **Column 4** - National Governors' Association,. (1998) How states can increase enrollment in the State Children's Health Insurance Program. In *NGA Online, NGA Issue Briefs* [Online]. Available: http://www.nga.org/Pubs/IssueBriefs/1998/980511IncreaseSCHIP.asp [1998, May 11]

Column 1 Comments

Income eligibility level is the percentage of the federal poverty level below which Medicaid covered the cost of pregnancy-related medical care.

† Value shown is eligibility level for the medically needy (if state had program for medically needy) or Aid to Families With Dependent Children eligibility level (if it did not).

* Prior to 1988, Arizona operated a medical assistance program under a Section 1115 demonstration waiver.

Column 2 Comments

Income eligibility level is for expanded coverage for pregnant women and infants as a percentage of the federal poverty level.

* These states had not yet expanded eligibility from previous levels.

Column 3 Comments

† Value shown is eligibility level for the medically needy (if state had program for medically needy) or Aid to Families With Dependent Children eligibility level (if it did not).

** State used its own funds to expand eligibility above 185%.

Column 4 Comments

Income eligibility level is for pregnant women and infants as a percentage of the federal poverty level.

*** Percentage NOT in brackets represents eligibility for pregnant women and percentage in brackets [ ] represents eligibility for infants.

†† Hawaii's coverage of pregnant women and children is through Hawaii QUEST, a Section 1115 waiver managed care program. Some populations receive fully subsidized services and other pay premiums. The state is considering a change in income eligibility that would take effect in late 1997. Pregnant women and infants living in families with incomes up to 185% of poverty would be eligible for fully subsidized Medicaid; children below six living in families with incomes up to 133% of poverty would be eligible; and older children living in families with incomes below 100% of poverty would be eligible.

††† Maryland, Minnesota, Rhode Island and Tennessee operate programs under Section 1115 waivers. Some populations receive fully subsidized Medicaid services. Other populations are required to pay a portion of the premium and may have a different benefits package.

Table 25. Medicaid eligibility and take-up rates[79] in the NMIHS sample by race

White			Black		
Eligibility rate	**Take-up rate**	**N**	**Eligibility rate**	**Take-up rate**	**N**
0.11	0.51	294	0.41	0.72	855

[79] The take-up rate is the percentage of Medicaid eligible women that participated in the Medicaid program.

Table 26. Summary of results from eligibility simulation

	Full results		Stratified by eligibility status in 1988 & 1997						Stratified by low birth weight			
			Eligible in 1988		*Eligible in 1997 ut not eligible in 1988*		*Not eligible in 1997*		*Low birth weight infant*		*Normal birth weight infant*	
	White N = 2562	Black N = 2106	White N = 294	Black N = 855	White N = 442	Black N = 499	White N = 1826	Black N = 752	White N = 564	Black N = 495	White N = 1998	Black N = 1611
Private insuranc predicted value i 1988	0.77 (0.14)	0.60 (0.16)	0.58 (0.14)	0.51 (0.06)	0.69 (0.17)	0.57 (0.14)	0.81 (0.09)	0.73 (0.16)	0.74 (0.16)	0.59 (0.15)	0.77 (0.14)	0.61 (0.16)
Private insuranc predicted value i 1997	0.71 (0.15)	0.49 (0.18)	0.51 (0.16)	0.43 (0.08)	0.62 (0.18)	0.49 (0.15)	0.77 (0.10)	0.68 (0.17)	0.69 (0.17)	0.53 (0.17)	0.72 (0.15)	0.54 (0.18)
Medicaid predicted value i 1988	0.53 (0.10)	0.66 (0.17)	0.65 (0.17)	0.78 (0.13)	0.55 (0.12)	0.66 (0.17)	0.50 (0.04)	0.54 (0.11)	0.55 (0.12)	0.67 (0.17)	0.52 (0.09)	0.66 (0.17)
Medicaid predicted value i 1997	0.79 (0.07)	0.81 (0.08)	0.81 (0.08)	0.83 (0.08)	0.83 (0.08)	0.82 (0.08)	0.78 (0.06)	0.78 (0.06)	0.78 (0.07)	0.80 (0.08)	0.80 (0.07)	0.81 (0.08)
Onset predicted value in 1988	8.37 (1.29)	9.51 (1.63)	9.78 (1.31)	10.27 (1.48)	9.11 (1.23)	10.09 (1.56)	7.97 (1.04)	9.02 (1.77)	8.53 (1.44)	9.91 (1.63)	8.34 (1.24)	9.74 (1.73)
Onset predicted value in 1997	8.28 (1.17)	9.30 (1.68)	9.44 (1.24)	9.86 (1.49)	8.87 (1.14)	9.73 (1.53)	7.95 (0.97)	8.91 (1.67)	8.42 (1.30)	9.61 (1.56)	8.24 (1.12)	9.45 (1.65)
Birth weight predicted value i 1988	3001.82 (294.29)	2911.02 (200.92)	2917.39 (357.46)	2866.83 (212.87)	2982.11 (317.41)	2868.09 (211.91)	3020.18 (274.04)	2868.29 (192.67)	2854.91 (280.42)	2804.37 (210.51)	3043.29 (284.75)	2887.09 (200.09)
Birth weight predicted value i 1997	2942.17 (285.16)	2908.84 (197.60)	2936.80 (340.83)	2944.17 (214.49)	2947.51 (307.18)	2896.55 (213.23)	2941.75 (269.54)	2818.96 (194.48)	2806.87 (268.25)	2827.55 (216.75)	2980.37 (278.15)	2906.80 (210.10)

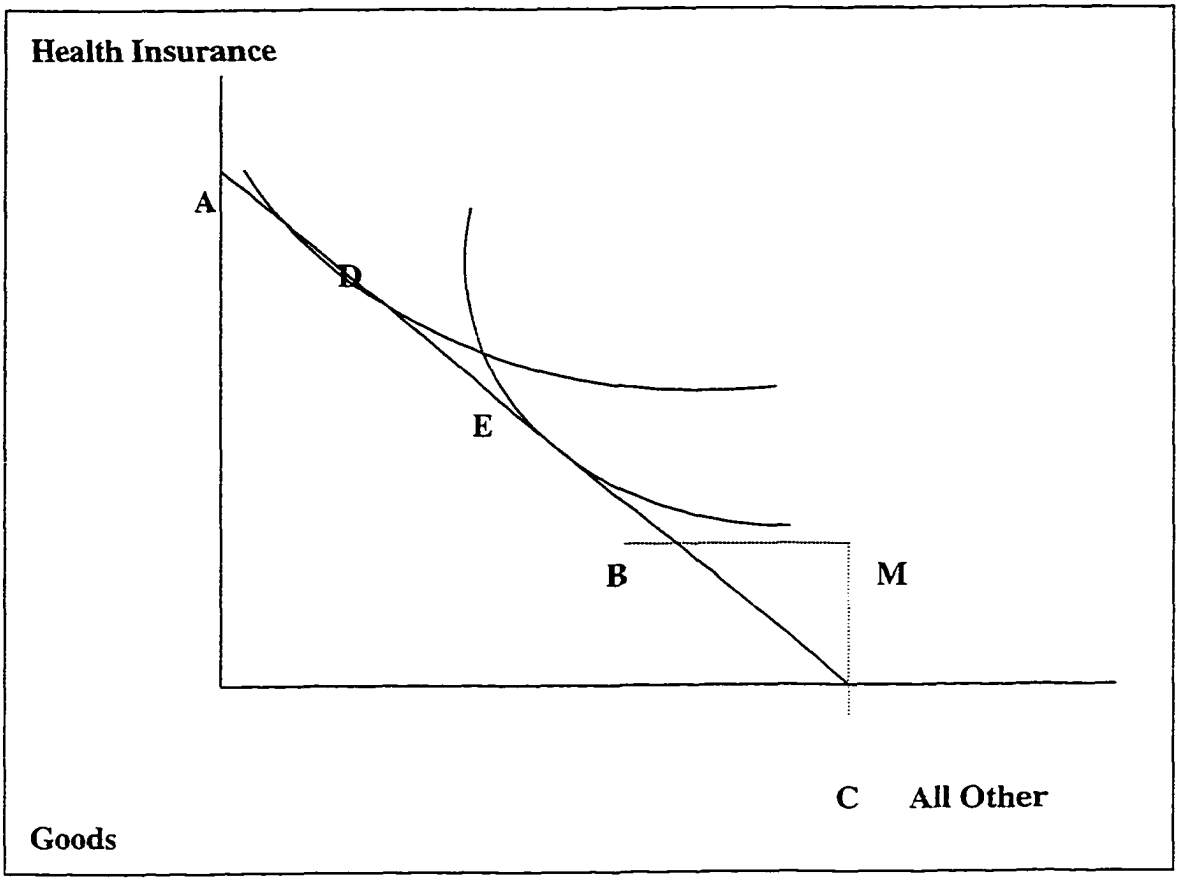
Standard deviations in parenthesis

Table 27. Summary of results from depression simulation

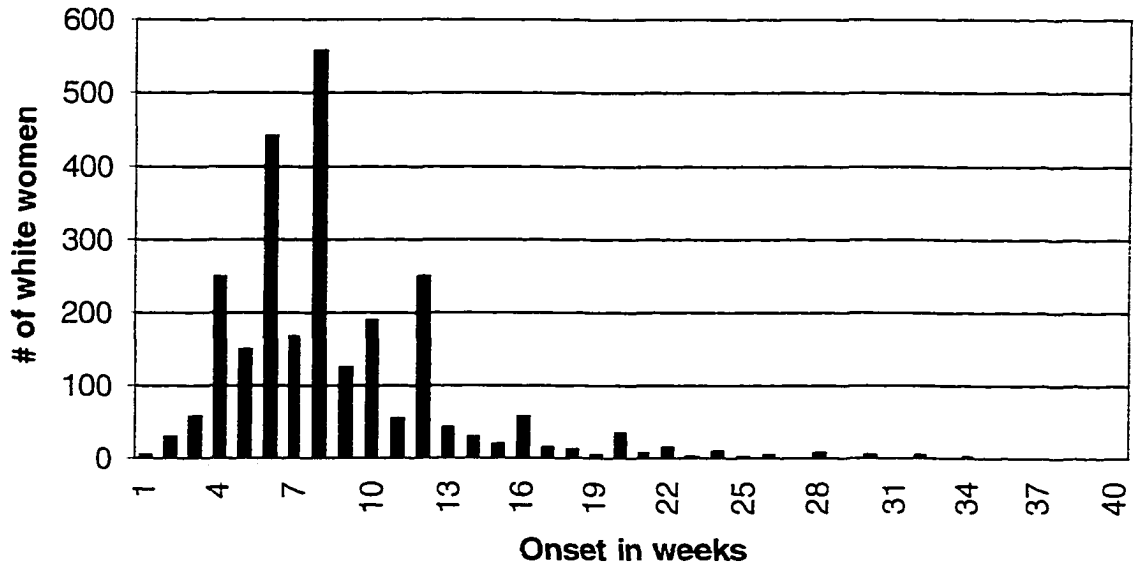
Cenosred observations (CESDavg > 16)						
			Low birth weight infant		*Normal birth weight infant*	
	White N = 380	Black N = 596	White N = 105	Black N = 148	White N = 275	Black N = 448
Private insurance predicted value in 1988	0.68 (0.17)	0.55 (0.12)	0.65 (0.17)	0.55 (0.11)	0.70 (0.17)	0.55 (0.12)
Private insurance predicted value in 1997	0.69 (0.17)	0.55 (0.12)	0.65 (0.17)	0.55 (0.11)	0.70 (0.17)	0.55 (0.12)
Medicaid predicted value in 1988	0.59 (0.15)	0.72 (0.16)	0.63 (0.17)	0.73 (0.16)	0.57 (0.14)	0.71 (0.17)
Medicaid predicted value in 1997	0.54 (0.15)	0.67 (0.17)	0.58 (0.17)	0.68 (0.17)	0.52 (0.14)	0.67 (0.18)
Onset predicted value in 1988	9.17 (1.45)	10.38 (1.54)	9.41 (1.53)	10.47 (1.38)	9.08 (1.41)	10.35 (1.60)
Onset predicted value in 1997	9.32 (1.21)	10.17 (1.42)	9.46 (1.26)	10.24 (1.28)	9.27 (1.19)	10.15 (1.47)
Birth weight predicted value in 1988	2877.92 (318.24)	2805.27 (221.34)	2709.64 (280.47)	2756.60 (240.31)	2942.17 (308.61)	2821.35 (212.55)
Birth weight predicted value in 1997	2882.45 (305.65)	2868.52 (219.76)	2732.70 (268.85)	2823.49 (229.35)	2939.63 (299.86)	2883.40 (214.69)
Number of white censored observations: 380 of 2562 (15%)						
Number of black censored observations: 596 of 2106 (28%)						
Mean of CESDavg for whites (before censoring): 8.79						
(after censoring): 7.75						
Mean of CESDavg for blacks (before censoring): 12.84						
(after censoring): 10.58						

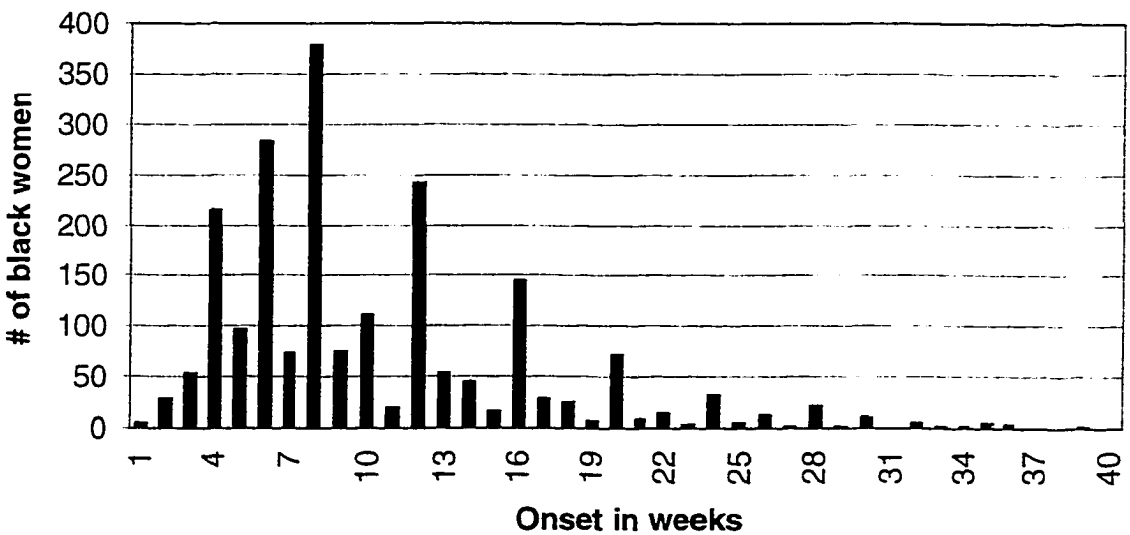
Standard deviations in parenthesis

Figure 1. The effect of public insurance on private insurance

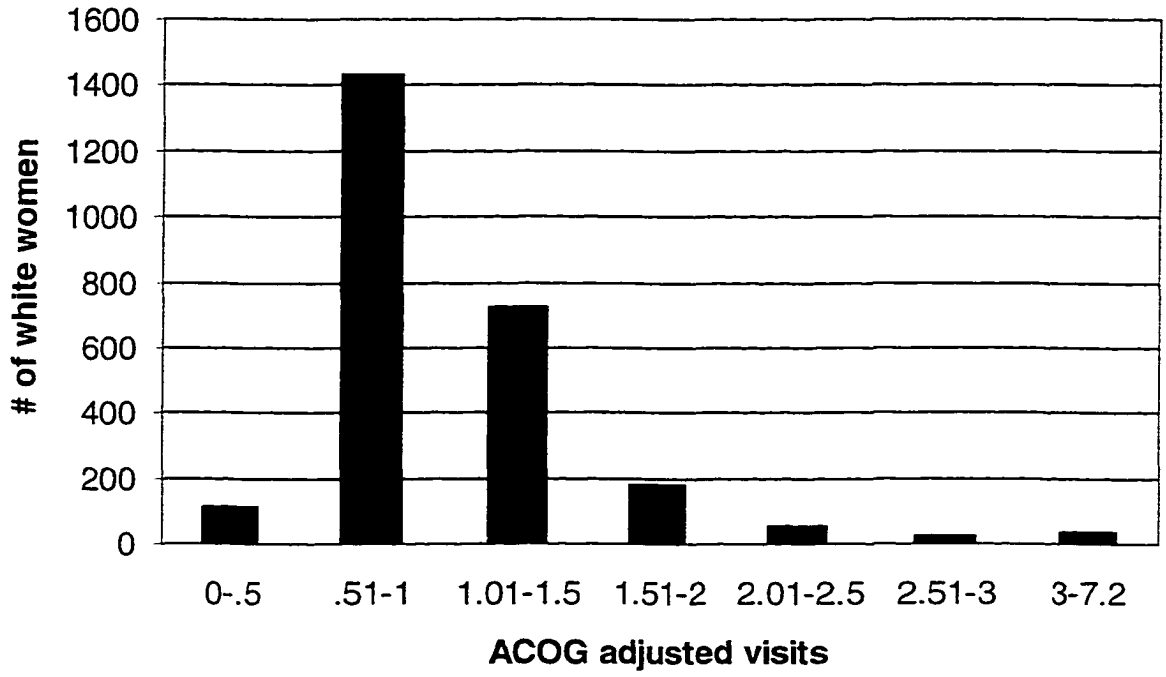


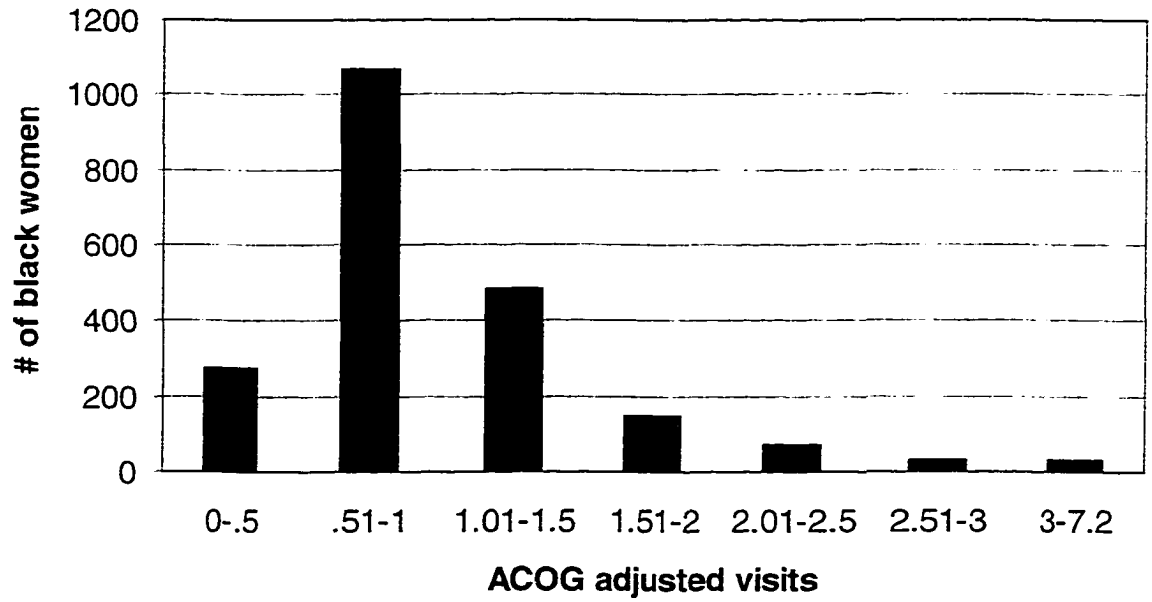
Figures 2 & 3. Distribution of the onset of prenatal care for white (N = 2562) and black women (N = 2106), respectively (in weeks from conception)



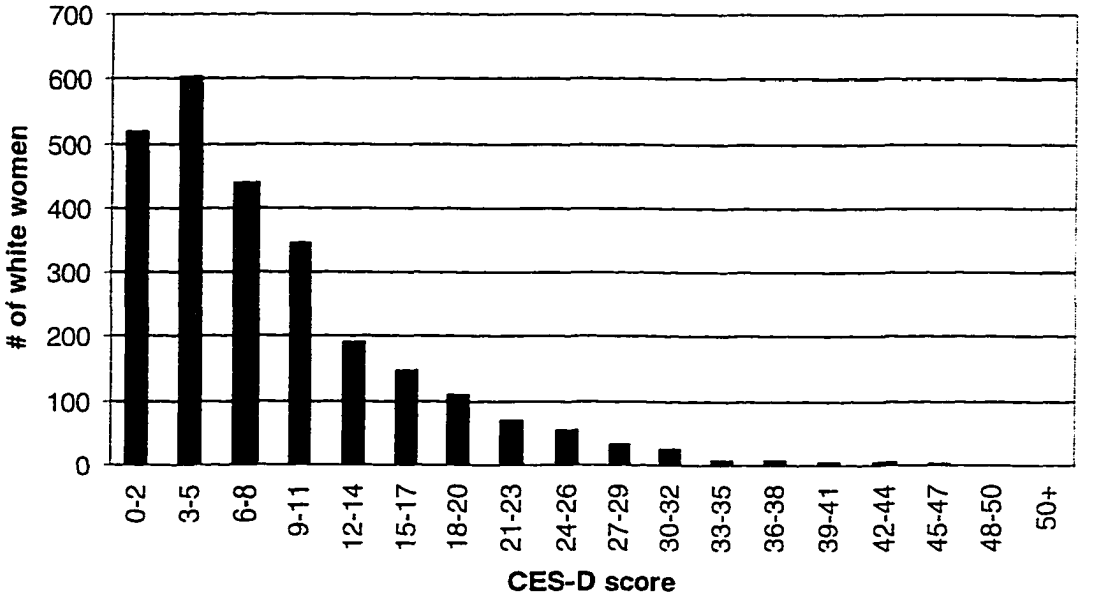


Figures 4 & 5. Distribution of the ACOG adjusted number of visits for white (N = 2562) and black women (N = 2106), respectively





Figures 6 & 7. Distribution of CES-D scores for white (N = 2562) and black women (N = 2106), respectively



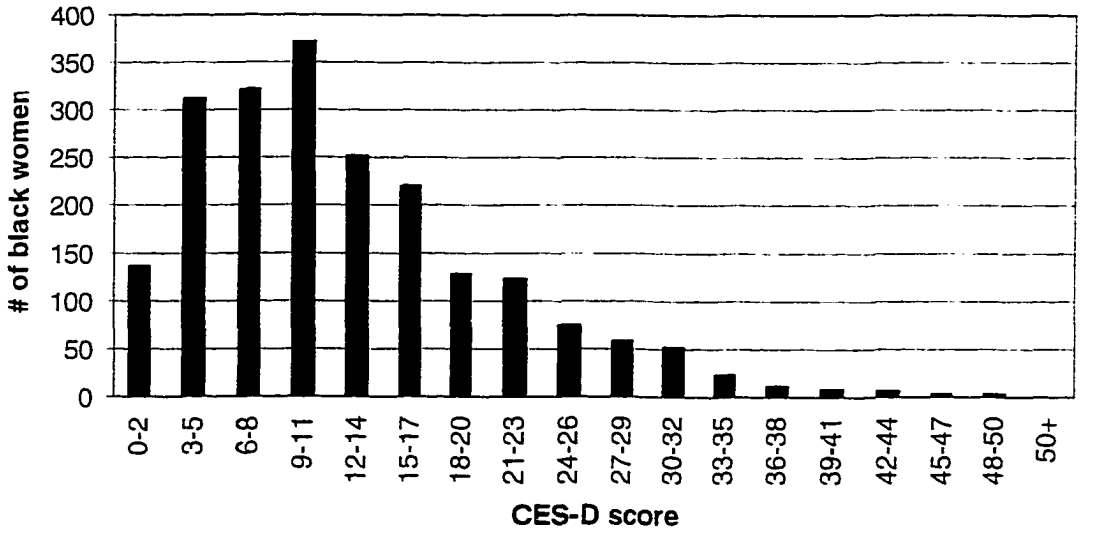


Figure 8. Overview of the three stages of the empirical model

Initial stage: Purpose is to correct for sample selection caused by using only a subset of the data on pregnant women - the sample of women that experienced a live birth. Heckman's 2-step is used to create the correction statistic, an inverse Mills ratio, that is included in all subsequent equations.

A. Estimate a reduced-form probability of birth equation using a probit:
Live Birth = 1 of live birth, 0 if infant/fetal death.
$Live\ Birth = f(X_{all})$ where X_{all} is all of the exogenous variables in the system.

B. Using the parameter estimates obtained from A. create an inverse Mills ratio:

$$\lambda(b'x) = \frac{\phi(b'x)}{1 - \Phi(b'x)}$$

This new variable is included as a regressor in all equations that appear in the next two-stages.

C. Since the NMIHS does not include abortion data, the NLSY is used to estimate the probit in **A.** The parameter estimates obtained from the NLSY are multiplied times the variables in the NMIHS in order to create the inverse Mills ratio. This is called a two-sample approach.

Stage two: Purpose is to control for the endogeneity bias created by the presence of Medicaid and private insurance. This means that these are choice variables - women can choose the type of insurance (including no insurance) that maximizes her utility. Similar to the initial stage. Heckman's 2-step is used to create inverse Mills ratios to correct for the endogeneity bias.

A. Estimate two reduced-form probability of insurance equations using two probits:
Medicaid = 1 if Medicaid pays for prenatal care, 0 otherwise.
Insurance = 1 if private insurance pays for prenatal care, 0 otherwise.
$MC, PI = f(X_{all})$ where X_{all} is all of the exogenous variables in the system.

B. Create 2 inverse Mills ratios as in the initial stage.

Final Stage: A treatment effects model simultaneously estimates prenatal care and birth weight (infant health) using two-stage least-squares (2SLS). The treatment effects model not only includes the inverse Mills ratios from the initial stage and stage two in each equation but also includes the actual values (0 or 1) of Medicaid and private insurance. Since the structural equation for birth weight is estimated, the prenatal care equation includes variables that identify birth weight.

A. Simultaneously estimate prenatal care, depression, and birth weight using 2SLS:
$Prenatal\ care = f(X, X^{identifiers}, \lambda_{LB}, \lambda_{MC}, \lambda_{PI}, MC, PI)$
$Birth\ weight = f(X, , \lambda_{LB}, \lambda_{MC}, \lambda_{PI}, MC, PI)$

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List of Appendices

Appendix 1
Derivation of standardized number of visits

The American College of Obstetrics and Gynecology (ACOG) recommends the following schedule of prenatal care visits:

A visit once a month during months 2-6
Visits twice a month during months 7-8
Visits weekly during the ninth month

I translated these rules into the recommended number of visits by day (rather than by month), according to the following schedule:

ACOG recommendation =
if 308<=days of gestation<=315 then ACOG recommended number of visits=18;
if 301<=days of gestation<308 then ACOG recommended number of visits=17;
if 294<=days of gestation<301 then ACOG recommended number of visits=16;
if 287<=days of gestation<294 then ACOG recommended number of visits=15;
if 280<=days of gestation<287 then ACOG recommended number of visits=14;
if 273<=days of gestation<280 then ACOG recommended number of visits=13;
if 266<=days of gestation<273 then ACOG recommended number of visits=12;
if 259<=days of gestation<266 then ACOG recommended number of visits=11;
if 252<=days of gestation<259 then ACOG recommended number of visits=10;
if 245<=days of gestation<252 then ACOG recommended number of visits=9;
if 230<=days of gestation<245 then ACOG recommended number of visits=8;
if 215<=days of gestation<230 then ACOG recommended number of visits=7;
if 200<=days of gestation<215 then ACOG recommended number of visits=6;
if 185<=days of gestation<200 then ACOG recommended number of visits=5;
if 155<=days of gestation<185 then ACOG recommended number of visits=4;
if 125<=days of gestation<155 then ACOG recommended number of visits=3;

The variable used in the model is the ratio between the actual number of prenatal visits and the ACOG recommended number of visits or

$$ACOGadj = \frac{\textit{actual number of prenatal visits}}{\textit{ACOG recommended number of prenatal visits}}$$

Appendix 2

Federal Poverty Guidelines[80] for the 48 Contiguous States and DC

POVERTY GUIDELINES BY FAMILY SIZE								
Year	1	2	3	4	5	6	7	8
1986	$5,360	$7,240	$9,120	$11,000	$12,880	$14,760	$16,640	$18,520
1987	$5,500	$7,400	$9,300	$11,200	$13,100	$15,000	$16,900	$18,800
1988	$5,770	$7,730	$9,690	$11,650	$13,610	$15,570	$17,530	$19,490
1989	$5,980	$8,020	$10,060	$12,100	$14,140	$16,180	$18,220	$20,260
1990	$6,280	$8,420	$10,560	$12,700	$14,840	$16,980	$19,120	$21,260
1991	$6,620	$8,880	$11,140	$13,400	$15,660	$17,920	$20,180	$22,440
1992	$6,810	$9,190	$11,570	$13,950	$16,330	$18,710	$21,090	$23,470
1993	$6,970	$9,430	$11,890	$14,350	$16,810	$19,270	$21,730	$24,190
1994	$7,360	$9,840	$12,320	$14,800	$17,280	$19,760	$22,240	$24,720
1995	$7,470	$10,030	$12,590	$15,150	$17,710	$20,270	$22,830	$25,390
1996	$7,740	$10,360	$12,980	$15,600	$18,220	$20,840	$23,460	$26,080
1997	$7,890	$10,610	$13,330	$16,050	$18,770	$21,490	$24,210	$26,930
1998	$8,050	$10,850	$13,650	$16,450	$19,250	$22,050	$24,850	$27,650

Federal Poverty Guidelines for Alaska

POVERTY GUIDELINES BY FAMILY SIZE								
Year	1	2	3	4	5	6	7	8
1986	$6,700	$9,050	$11,400	$13,750	$16,100	$18,450	$20,800	$23,150
1987	$6,860	$9,240	$11,620	$14,000	$15,380	$18,760	$21,140	$23,520
1988	$7,210	$9,660	$12,110	$14,560	$17,010	$19,460	$21,910	$24,360
1989	$7,480	$10,030	$12,580	$15,130	$17,680	$20,230	$22,780	$25,330
1990	$7,840	$10,520	$13,200	$15,880	$18,560	$21,240	$23,920	$26,600
1991	$8,290	$11,110	$13,930	$16,750	$19,570	$22,390	$25,210	$28,030
1992	$8,500	$11,480	$14,460	$17,440	$20,420	$23,400	$26,380	$29,360
1993	$8,700	$11,730	$14,860	$17,940	$21,020	$24,100	$27,180	$30,260
1994	$9,200	$12,300	$15,400	$18,500	$21,600	$24,700	$27,800	$30,900
1995	$9,340	$12,540	$15,740	$18,940	$22,140	$25,340	$28,540	$31,740
1996	$9,660	$12,940	$16,220	$19,500	$22,780	$26,060	$29,340	$32,620
1997	$9,870	$13,270	$16,670	$20,070	$23,470	$26,870	$30,270	$33,670
1998	$10,07	$13,570	$17,070	$20,570	$24,070	$27,570	$31,070	$34,570

Federal Poverty Guidelines for Hawaii

Year	1	2	3	4	5	6	7	8
1986	$6,170	$8,330	$10,490	$12,650	$14,810	$16,970	$19,130	$21,290
1987	$6,310	$8,500	$10,690	$12,880	$15,070	$17,260	$19,450	$21,640
1988	$6,650	$8,900	$11,150	$13,400	$15,650	$17,900	$20,150	$22,400
1989	$6,870	$9,220	$11,570	$13,920	$16,270	$18,620	$20,970	$23,320
1990	$7,230	$9,690	$12,150	$14,610	$17,070	$19,530	$21,990	$24,450
1991	$7,610	$10,210	$12,810	$15,410	$18,010	$20,610	$23,210	$25,810
1992	$7,830	$10,570	$13,310	$16,050	$18,790	$21,530	$24,270	$27,010
1993	$8,040	$10,860	$13,680	$16,500	$19,320	$22,140	$24,960	$27,780
1994	$8,470	$11,320	$14,170	$17,020	$19,870	$22,720	$25,570	$28,420
1995	$8,610	$11,550	$14,490	$17,430	$20,370	$23,310	$26,250	$29,190
1996	$8,910	$11,920	$14,930	$17,940	$20,950	$23,960	$26,970	$29,980
1997	$9,070	$12,200	$15,330	$18,460	$21,590	$24,720	$27,850	$30,980
1998	$9,260	$12,480	$15,700	$18,920	$22,140	$25,360	$28,580	$31,800

[80] **Source**: Federal Register, Annual Update of the HHS Poverty Guidelines, various years.

Appendix 3

State-Level Medicaid Eligibility (in Dollars) By Family Size

Family Size = 1

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988[81]	1997	State	1988	1997
AL	$5,770	$10,494	MT*	$3,070	$10,494
AK	$7,210	$13,127	NE	$5,770	$11,835
AZ	$5,770	$11,046	NV*	$2,164	$10,494
AR	$5,770	$10,494 [$15,780]	NH*	$3,543	$14,597
CA*	$6,266	$15,780	NJ	$5,770	$14,597
CO*	$3,197	$10,494	NM	$5,770	$14,597
CT	$10,675	$14,597	NY*	$4,616	$14,597
DE	$5,770	$14,597	NC	$5,770	$14,597
DC	$5,770	$14,597	ND*	$3,300	$10,494
FL	$5,770	$14,597	OH	$5,770	$10,494
GA	$5,770	$14,597	OK	$5,770	$11,835
HI	$6,650	$27,210	OR	$5,770	$10,494
ID	$3,866	$10,494	PA	$5,770	$14,597
IL	$5,770	$10,494	RI	$10,675	$19,725
IN	$2,885	$11,835	SC	$5,770	$14,597
IA	$8,655	$14,597	SD	$5,770	$10,494
KS	$5,770	$11,835	TN	$5,770	$31,560
KY	$7,213	$14,597	TX	$5,770	$14,597
LA	$5,770	$10,494	UT	$5,770	$10,494
ME	$10,675	$14,597	VT	$10,675	$15,780 [$17,753]
MD	$5,770	$14,597	VA	$5,770	$10,494
MA	$10,675	$14,597	WA	$5,193	$14,597 [$15,780]
MI	$10,675	$14,597	WV	$8,655	$11,835
MN	$10,675	$21,698	WI*	$4,864	$14,597
MS	$10,675	$14,597	WY	$5,770	$10,494
MO	$5,770	$14,597			

* Since these states had not yet undergone the 1988 expansions, eligibility levels are from December 1996.

[81] The Medicaid eligibility levels used are based on data from April 1987-January 1989.

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 2

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$7,730	$14,111	MT	$4,112	$14,111
AK	$9,660	$17,649	NE	$7,730	$15,915
AZ	$7,730	$14,854	NV	$2,899	$14,111
AR	$7,730	$14,111 [21,220]	NH	$4,746	$19,629
CA	$‘8,395	$21,220	NJ	$7,730	$19,629
CO	$4,282	$14,111	NM	$7,730	$19,629
CT	$14,301	$19,629	NY	$6,184	$19,629
DE	$7,730	$19,629	NC	$7,730	$19,629
DC	$7,730	$19,629	ND	$4,422	$14,111
FL	$7,730	$19,629	OH	$7,730	$14,111
GA	$7,730	$19,629	OK	$7,730	$15,915
HI	$8,900	$36,600	OR	$7,730	$14,111
ID	$5,179	$14,111	PA	$7,730	$19,629
IL	$7,730	$14,111	RI	$14,301	$26,525
IN	$3,865	$15,915	SC	$7,730	$19,629
IA	$11,595	$19,629	SD	$7,730	$14,111
KS	$7,730	$15,915	TN	$7,730	$42,440
KY	$9,663	$19,629	TX	$7,730	$19,629
LA	$7,730	$14,111	UT	$7,730	$14,111
ME	$14,301	$19,629	VT	$14,301	$21,220 [23,873]
MD	$7,730	$19,629	VA	$7,730	$14,111
MA	$14,301	$19,629	WA	$6,957	$19,629 [21,220]
MI	$14,301	$19,629	WV	$11,595	$15,915
MN	$14,301	$29,178	WI	$6,516	$19,629
MS	$14,301	$19,629	WY	$7,730	$14,111
MO	$7,730	$19,629			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 3

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$9,690	$17,729	MT	$5,155*	$17,729
AK	$12,110	$22,171	NE	$9,690	$19,995
AZ	$9,690	$18,662	NV	$3,634*	$17,729
AR	$9,690	$17,729 [26,660]	NH	$5,950*	$24,661
CA	$10,523*	$26,660	NJ	$9,690	$24,661
CO	$5,368*	$17,729	NM	$9,690	$24,661
CT	$17,927	$24,661	NY	$7,752*	$24,661
DE	$9,690	$24,661	NC	$9,690	$24,661
DC	$9,690	$24,661	ND	$5,542*	$17,729
FL	$9,690	$24,661	OH	$9,690	$17,729
GA	$9,690	$24,661	OK	$9,690	$19,995
HI	$11,150	$45,990	OR	$9,690	$17,729
ID	$6,492	$17,729	PA	$9,690	$24,661
IL	$9,690	$17,729	RI	$17,927	$33,325
IN	$4,845	$19,995	SC	$9,690	$24,661
IA	$14,535	$24,661	SD	$9,690	$17,729
KS	$9,690	$19,995	TN	$9,690	$53,320
KY	$12,113	$24,661	TX	$9,690	$24,661
LA	$9,690	$17,729	UT	$9,690	$17,729
ME	$17,927	$24,661	VT	$17,927	$26,660 [29,993]
MD	$9,690	$24,661	VA	$9,690	$17,729
MA	$17,927	$24,661	WA	$8,721	$24,661 [26,660]
MI	$17,927	$24,661	WV	$14,535	$19,995
MN	$17,929	$36,658	WI	$8,169*	$24,661
MS	$17,927	$24,661	WY	$9,690	$17,729
MO	$9,690	$24,661			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 4

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$11,650	$21,347	MT	$6,198	$21,347
AK	$14,560	$26,693	NE	$11,650	$24,075
AZ	$11,650	$22,470	NV	$4,369	$21,347
AR	$11,650	$21,347 [32,100]	NH	$7,153	$29,693
CA	$12,652	$32,100	NJ	$11,650	$29,693
CO	$6,454	$21,347	NM	$11,650	$29,693
CT	$21,553	$29,693	NY	$9,320	$29,693
DE	$11,650	$29,693	NC	$11,650	$29,693
DC	$11,650	$29,693	ND	$6,664	$21,347
FL	$11,650	$29,693	OH	$11,650	$21,347
GA	$11,650	$29,693	OK	$11,650	$24,075
HI	$13,400	$55,380	OR	$11,650	$21,347
ID	$7,806	$21,347	PA	$11,650	$29,693
IL	$11,650	$21,347	RI	$21,553	$40,125
IN	$5,825	$24,075	SC	$11,650	$29,693
IA	$17,475	$29,693	SD	$11,650	$21,347
KS	$11,650	$24,075	TN	$11,650	$64,200
KY	$14,563	$29,693	TX	$11,650	$29,693
LA	$11,650	$21,347	UT	$11,650	$21,347
ME	$21,553	$29,693	VT	$21,553	$32,100 [36,113]
MD	$11,650	$29,693	VA	$16,050	$21,347
MA	$21,553	$29,693	WA	$10,485	$29,693 [32,100]
MI	$21,553	$29,693	WV	$17,475	$24,075
MN	$21,553	$44,138	WI	$9,821	$29,693
MS	$21,553	$29,693	WY	$11,650	$21,347
MO	$11,650	$29,693			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 5

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$13,610	$24,964	MT	$7,241	$24,964
AK	$17,010	$31,215	NE	$13,610	$28,155
AZ	$13,610	$26,278	NV	$5,104	$24,964
AR	$13,610	$24,964 [37,540]	NH	$8,357	$34,725
CA	$14,780	$37,540	NJ	$13,610	$34,725
CO	$7,540	$24,964	NM	$13,610	$34,725
CT	$25,179	$34,725	NY	$10,888	$34,725
DE	$13,610	$34,725	NC	$13,610	$34,725
DC	$13,610	$34,725	ND	$7,785	$24,964
FL	$13,610	$34,725	OH	$13,610	$24,964
GA	$13,610	$34,725	OK	$13,610	$28,155
HI	$15,650	$64,770	OR	$13,610	$24,964
ID	$9,119	$24,964	PA	$13,610	$34,725
IL	$13,610	$24,964	RI	$25,179	$46,925
IN	$6,805	$28,155	SC	$13,610	$34,725
IA	$20,415	$34,725	SD	$13,610	$24,964
KS	$13,610	$28,155	TN	$13,610	$75,080
KY	$17,013	$34,725	TX	$13,610	$34,725
LA	$13,610	$24,964	UT	$13,610	$24,964
ME	$25,179	$34,725	VT	$25,179	$37,540 [42,233]
MD	$13,610	$34,725	VA	$13,610	$24,964
MA	$25,179	$34,725	WA	$12,249	$34,725 [37,540]
MI	$25,179	$34,725	WV	$20,415	$28,155
MN	$25,179	$34,725	WI	$11,473	$34,725
MS	$25,179	$34,725	WY	$13,610	$24,964
MO	$13,610	$24,964			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 6

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$15,570	$28,582	MT	$8,283	$28,582
AK	$19,460	$35,737	NE	$15,570	$32,235
AZ	$15,570	$30,086	NV	$5,839	$28,582
AR	$15,570	$28,582	NH	$9,560	$39,757
CA	$16,909	$42,980	NJ	$15,570	$39,757
CO	$8,626	$28,582	NM	$15,570	$39,757
CT	$28,805	$39,757	NY	$12,456	$39,757
DE	$15,570	$39,757	NC	$15,570	$39,757
DC	$15,570	$39,757	ND	$8,906	$28,582
FL	$15,570	$39,757	OH	$15,570	$28,582
GA	$15,570	$39,757	OK	$15,570	$32,235
HI	$17,900	$74,160	OR	$15,570	$28,582
ID	$10,432	$28,582	PA	$15,570	$39,757
IL	$15,570	$28,582	RI	$28,805	$53,725
IN	$7,785	$32,235	SC	$15,570	$39,757
IA	$23,355	$39,757	SD	$15,570	$28,582
KS	$15,570	$32,235	TN	$15,570	$85,960
KY	$19,463	$39,757	TX	$15,570	$39,757
LA	$15,570	$28,582	UT	$15,570	$28,582
ME	$28,805	$39,757	VT	$28,805	$42,980 [$48,353]
MD	$15,570	$39,757	VA	$15,570	$28,582
MA	$28,805	$39,757	WA	$14,013	$39,757 [$42,980]
MI	$28,805	$39,757	WV	$23,355	$32,235
MN	$28,805	$59,098	WI	$13,126	$39,757
MS	$28,805	$39,757	WY	$15,570	$28,582
MO	$15,570	$39,757			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 7

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$17,530	$32,199	MT	$9,326	$32,199
AK	$21,910	$40,259	NE	$17,530	$24,210
AZ	$17,530	$33,894	NV	$6,521	$32,199
AR	$17,530	$32,199	NH	$10,763	$44,789
CA	$19,038	$48,420	NJ	$17,530	$24,210
CO	$9,712	$32,199	NM	$17,530	$24,210
CT	$32,431	$44,789	NY	$14,024	$24,210
DE	$17,530	$44,789	NC	$17,530	$24,210
DC	$17,530	$44,789	ND	$10,027	$32,199
FL	$17,530	$44,789	OH	$17,530	$32,199
GA	$17,530	$44,789	OK	$17,530	$24,210
HI	$20,150	$83,550	OR	$17,530	$32,199
ID	$11,745	$32,199	PA	$17,530	$24,210
IL	$17,530	$32,199	RI	$32,431	$60,525
IN	$8,765	$36,315	SC	$17,530	$44,789
IA	$26,295	$44,789	SD	$17,530	$32,199
KS	$17,530	$36,315	TN	$17,530	$96,840
KY	$21,913	$44,789	TX	$17,530	$44,789
LA	$17,530	$32,199	UT	$17,530	$32,199
ME	$32,431	$44,789	VT	$32,431	$48,420 [54,473]
MD	$17,530	$44,789	VA	$17,530	$32,199
MA	$32,431	$44,789	WA	$15,777	$45,757 [48,420]
MI	$32,431	$44,789	WV	$26,295	$36,315
MN	$32,431	$66,578	WI	$14,778	$44,789
MS	$32,431	$44,789	WY	$17,530	$32,199
MO	$17,530	$44,789			

State-Level Medicaid Eligibility (in Dollars) By Family Size
Family Size = 8

Income Eligibility Levels as a Function of % of Poverty			Income Eligibility Levels as a Function of % of Poverty		
State	1988	1997	State	1988	1997
AL	$19,490	$35,817	MT	$10,369	$35,817
AK	$24,360	$44,781	NE	$19,490	$40,395
AZ	$19,490	$37,702	NV	$7,250	$35,817
AR	$19,490	$35,817	NH	$11,967	$49,821
CA	$21166	$53,860	NJ	$19,490	$49,821
CO	$10797	$35,817	NM	$19,490	$49,821
CT	$36057	$49,821	NY	$15,592	$49,821
DE	$19,490	$49,821	NC	$19,490	$49,821
DC	$19,490	$49,821	ND	$11,148	$35,817
FL	$19,490	$49,821	OH	$19,490	$35,817
GA	$19,490	$49,821	OK	$19,490	$40,395
HI	$22,400	$92,940	OR	$19,490	$35,817
ID	$13058	$35,817	PA	$19,490	$49,821
IL	$19,490	$35,817	RI	$36,057	$67,325
IN	$9,745	$40,395	SC	$19,490	$49,821
IA	$29,235	$49,821	SD	$19,490	$35,817
KS	$19,490	$40,395	TN	$19,490	$107,720
KY	$24,363	$49,821	TX	$19,490	$49,821
LA	$19,490	$35,817	UT	$19,490	$35,817
ME	$36,057	$49,821	VT	$36057	$53,860 [$60,593]
MD	$19,490	$49,821	VA	$19,490	$35,817
MA	$36,057	$49,821	WA	$17,541	$49,821 [$53,860]
MI	$36,057	$49,821	WV	$29,235	$40,395
MN	$36,057	$74,058	WI	$16,430	$49,821
MS	$36,056	$49,821	WY	$19,490	$35,817
MO	$19,490	$49,821			

Appendix 4

Sample calculation of imputing a woman's Medicaid eligibility in 1988

This calculation is a very rough estimate of whether a woman is considered Medicaid eligible. A more accurate estimate would require both comprehensive data on each woman and a detailed account of state-by-state eligibility rules.

Step One. Determine a woman's household size. This is computed by summing the number of children living in the woman's household and herself. Typically, a woman's husband or boyfriend does not count in determining eligibility.

Eg. Woman has 3 children living in household, yielding a household size of four.

Step Two. Determine a woman's state of residence.

Eg. Woman lives in Alabama.

Step Three. Determine the federal poverty level (FPL) income for a household size of four, living in Alabama, in 1988. Refer to **Appendix 2** for a list of the FPLs.

Eg. The FPL for a household of four, living in Alabama, in 1988 is $11,650.

Step Four. Determine the Medicaid income eligibility level for Alabama in 1988. See **Table 12** (or **Appendix 3**) for a list.

Eg. In Alabama, in 1988, the income eligibility level is 100% of the FPL.

Step Five. Multiply the percentage allowed by the FPL (i.e. Step 4 x Step 5). This gives the maximum allowable income in order to be Medicaid eligible.

Eg. 100% x $11,650 = $11,650.

Step Six. Compare a woman's annual household income to the maximum allowable income. If she earns less than the maximum, she is Medicaid eligible. If she earns more, she is ineligible.

Eg. Woman income = $10,000 < $11,650. Therefore, she is Medicaid eligible.

In order to determine whether the woman participates in Medicaid (this measure in the aggregate is the Medicaid take-up rate):

Step Seven. If a woman is eligible and the Medicaid dummy variable = 1, then she participates. (Aggregating this across all eligible women determines the take-up rate).

Eg. Woman is eligible and Medicaid = 0, then she does not take-up Medicaid.