An Econometric Model of Birth Inputs and Outputs

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Abstract

This study offers a simultaneous equations model of the birth process with seven endogenous variables: four birth inputs [***maternal smoking (S)***, ***maternal drinking (D)***, ***first trimester prenatal care (PC)***, and ***maternal weight gain (WG)***], and three birth outputs [***gestational age (G)***, ***birth length (BL)***, and ***birth weight (BW)***]. Our analysis conditions on twenty-four exogenous variables. The data are taken from the NLSY. Separate analyses are performed on five different groups: Whites (both the Main and the Supplemental samples), Blacks, Hispanics, and Native Americans. Across all groups, we find sizeable correlation between the disturbances in the four input and three output equations and among output disturbances. *Ceteris Paribus*, the effect of maternal smoking on BL and BW is negative, the effect of weight gain on BL and BW is positive, long gestation has a favorable effect on both BL and BW, a male infant is longer and heavier than a female infant, and maternal height and weight have a positive effect on BL and BW, respectively. Surprisingly, we find that the widely-cited group differences in birth outputs can be accommodated in our framework with simple group dummies. Our framework also sheds some light on the High/Low Risk Birth Weight Puzzle discussed in the literature. Finally, our results are robust with respect to different model and prior specifications.

Key words: Bayesian, birth length, birth weight, gestation, NLSY, simultaneity

1. Introduction

1.1 Background

This paper and its detailed companions, Li and Poirier (1999, 2000), draw on two disparate literatures on ***birth weight (BW)***: economics and biomedical. The primary distinguishing feature between the two is that the economics literature, unlike the biomedical, views many aspects of maternal behavior, together with BW and related birth outputs, as ***endogenous*** to the birth process,

i.e., they are determined within the system under analysis.

BW is probably the single most important indicator of infant health [Institute of Medicine (1985)]. It is also a significant predictor of infant mortality, morbidity, coronary heart disease, neurodevelopmental handicaps, and learning disabilities [e.g., Illsley and Mitchell (1984) and Poirier (1998)]. Infants weighing less than 2,500 grams (g) (5 pounds, 8 ounces) are commonly referred to as ***low birth weight (LBW)*** infants. LBW infants are almost 40 times more likely to die during their first 4 weeks of life than normal BW infants. ***Very low birth weight (VLBW)*** infants are defined as infants with BW < 1,500g (3 pounds, 5 ounces). Risk of neonatal death is 200 times greater for VLBW infants than for normal BW infants.

BW is the result of two processes: (i) the ***gestational age (G)***, and (ii) the intrauterine growth rate of the fetus. LBW is the result of short gestation (prematurity) and/or ***intrauterine growth retardation (IUGR)***. Gestational age is hard to measure. The mother's recollection of her ***last normal menstrual period (LNMP)*** is recommended by the World Health Organization to determine pregnancy duration. We assume G is two weeks shorter than the period elapsed since LNMP.

IUGR is usually defined to occur when BW is less than the tenth percentile for the given gestational age. Most LBW infants and nearly all VLBW infants are preterm. Preterm birth and IUGR appear to have different determinants and different impacts on infant mortality rates [Kramer (1987, p. 718), Miller and Merritt (1979), and Paneth (1995)]. Therefore, combining BW and prematurity simply into LBW or VLBW is potentially misleading. In this paper we treat both BW and G as endogenous in the birth process.

More is known about the determinants of fetal growth and IUGR than about those of G [Kramer (1987)]. Kramer (1990, p. 383) argues that the three main risk factors of IUGR (maternal smoking, low caloric intake or gestational weight gain, and low prepregnancy weight) are all

modifiable. Unfortunately, this is not the case for preterm birth. Lieberman et al. (1987), McCormick (1991, p. 4) and Verloove-Vanhorick et al. (1986) conclude that neonatal outcome is better predicted by gestational age than by BW.

Miller and Merritt (1979) forcefully argue that measurements of crown-heel length, head circumference, mid-arm circumference, and skinfolds or other indices of body fat are also important data that should be recorded together with BW and G for purpose of predicting future morbidity outcomes. In this paper we work with three birth outputs: BW, G, and ***birth length (BL)***.

1.2 The View of Economists

Economists view BW in the context of a process in which the mother acts as a decision-maker striving to achieve goals subject to constraints. Maternal behavior provides a variety of inputs into the production of birth outcomes. This empowerment of the mother as a decision-maker may take on a highly formal framework in which the mother, say, sequentially maximizes discounted expected utility (assumed to be a function of the health of her children and herself, her labor supply, and standard commodities), given the realization of birth outcomes of previous children, and subject to feasibility and informational constraints reflecting the socioeconomic/cultural environment in which she lives. Hotz, Klerman and Willis (1997) provide an excellent recent survey of this view.

Such extreme formalism is ***not*** the goal here, but it does motivate two crucial points. Firstly, BW is but one of many ***endogenous*** outcomes of the birth process. Secondly, the purposeful behavior of the mother in striving for a healthy infant creates demands for health inputs (e.g., whether to smoke, drink, use drugs, obtain prenatal care, etc.) into a ***three-output birth production function (BPF)***. The BPF represents the technical (biological/physiological) relationship between the birth outputs G, BL, and BW and the birth inputs discussed below. The inputs are determined by ***health input demand functions*** which describe input choices subject to the constraints the mother faces. The

essence of economists' views is that the mother is attempting to do the best that she can for herself and her child subject to the multiple constraints she faces.

The endogeneity of inputs in the BPF is the important distinguishing statistical feature between the economists' models and those of other social scientists and epidemiologists. The primary statistical implication of the economists' viewpoint is that regressing BW on measures of ***smoking (S), drinking alcohol (D)***, ***seeking prenatal care in the first trimester (PC)***, and proper maternal nutrition as measured by ***weight gain (WG)*** net of BW, is has little relevance for policy analysis. Instead it is necessary to consider ***simultaneous*** modeling of the many endogenous aspects of the birth process, in order to place BW in its proper context as a useful indicator of health outcomes of more primary importance (e.g., infant mortality).

1.3 Racial/Ethnic Differences in Birth Outputs

The racial/ethnic differences in the univariate distributions of BW are striking [Poirier (1998)]. The rates of LBW and VLBW for Blacks are more than twice those of Whites and Asians. Similarly, Blacks have much higher rates of preterm births [Rowley and Tosteson (1993)]. There has been relatively little change in the U.S. BW distribution. The frequency of VLBW infants has not declined since 1970, especially for births below 500g [Kleinman (1990) and Wilson, Fenton and Munson (1986)]. In fact, there has been an ***increase*** of VLBW infants among Blacks.

Paradoxically, the excess risk for LBW among Black as compared with White women is ***greater*** among low-risk mothers than among high-risk mothers [e.g., Gates-Williams et al. (1995), Kleinman and Kessel (1987), Lieberman (1995, p. 117)]. According to Ventura et al. (1995, p. 20), Black college-educated mothers with the recommended weight gain, timely prenatal care, and at least 18 months since their last live birth are 2½ times as likely to have a term LBW infant as White women with similar pregnancy-risk characteristics. We refer to this as the ***High/Low Risk Birth***

Weight Puzzle. Section 4.8 investigates its applicability to other groups vis-a-via Whites.

Since relatively little is understood from the clinical/epidemiological side regarding what affects G, BL, and BW, it is difficult to trace the roots of racial/ethnic differences. See Kempe et al. (1992, p. 972) and Lieberman (1995, p. 117) for discussions of the conflicting evidence. It is difficult to find variables to condition upon so that the Black-White discrepancy in BW disappears [e.g., Institute of Medicine (1985, p. 56)]. We will return to this point in Section 4.8.

In summary, for policy purposes the socioeconomic and cultural aspects of race/ethnicity are more important than the genetic and biological aspects. We initially treat Whites, Blacks, Hispanics, and Native Americans separately, and then we investigate whether pooling is appropriate. We judge the number of Asian births in our data set, thirty-three, as too small for meaningful analysis.

2. Data

The statistical window to be described in Section 3.2 is quite ambitious compared to counterparts in the biomedical literature on BW, and so it requires a very rich data set for implementation. Fortunately, the data set commonly used by social scientists, the National Longitudinal Survey of Youth (NLSY) is up to the task. The NLSY is an ongoing study of 12,686 young men and women aged 14 to 21 as of January 1, 1979. Over 90% of these respondents have participated in an annual personal interview, approximately one hour in length, since 1979. Individuals are followed after leaving their baseline household. There is relatively little attrition.

Racial/ethnic groups are defined by the mother's self-reported identification. NLSY data comprise both random cross-sectional sampling and supplemental sampling of individuals. We begin by analyzing each group separately for both types of samples, and we test the legitimacy of pooling the main cross-sectional and supplemental samples in the case of Blacks and of Hispanics. The

supplemental sample for Whites is expected to differ from the Main White sample: by design it contains "disadvantaged" White individuals. The supplemental sampling of Blacks and Hispanics is intended to obtain adequate sample sizes for these groups. In anticipation of the pooling tests that are done in Section 4.2, the Main and Supplemental samples are combined for Blacks and Hispanics in all tables that follow. Hereafter we refer to these five subsets (Main White, Supplemental White, Black, Hispanic and Native American) as ***groups***. Further pooling of groups is also investigated in Section 4.2.

We analyze only ***singleton first-born live births***, leaving aside sample selection problems arising from parity considerations and abortions. There were 3,648 live singleton first births to White, Black, Hispanic, and Native American women between 1979 and 1994 in the NLSY. We dropped 221 births to women in the military and 28 to women no longer living in the U.S.A. This left 3,399 observations for our target sample. Missing observations [described in Li and Poirier (2000, Table 1)] further reduced our sample to 1,962 observations with complete data (57.7% of our target sample).

Table 1 contains the sample means of the endogenous variables together with the sample standard deviations of the mean in parentheses and the sample standard deviation of the variable itself in square brackets. Table 2 contains the sample means of all twenty-four exogenous variables together with the sample standard deviations of the mean in parentheses. Li and Poirier (2000) contains a detailed description of the variables involved. Our Black mothers have favorable birth outcomes compared to Blacks at large [Ventura et al. (1999)]. Figures 1-3 contain univariate histograms of the three outputs (G, BL, and BW) for each group.

Our choice of the exogenous (conditioning) variables in Table 2 is guided by the existing literature. Variables x_2 - x_6 cover basic physical characteristics (the gender of the infant, the age and

size of the mother) which we expect to be very important in the birth output equations. We are not trying to explain fertility, and so we are not trying to explain the mother's pregnancy. Hence, variables like maternal age (x_6) are properly treated as exogenous in our analysis. Following biomedical tradition, physical characteristics of the father are omitted [Basso, Olsen, and Christensen (1999)]. Variables x_7 - x_{12} capture regional and temporal effects plus the intelligence and family income of the mother. Variables x_{13} - x_{25} capture health insurance status and a variety of socioeconomic measures of the mother's family background. Variables x_7 - x_{25} are risk factors that causally are quite far removed from the biological event of LBW. We expect these variables to be important in the input equations, but not in the biologically based output equations.

We have centered the variables in Table 2 in such a way to impart a meaningful interpretation to the intercepts in our model. The case in which all elements of x_i other than x_{i1} are zero describes generically a mother we will refer to as our ***reference mother***. This reference mother is twenty-three years old, lives in the north-central region, gives birth to a female infant in January 1985, has access to health insurance, lives with another adult, has a household income of $25,000, has a ***body mass index*** (BMI = weight in kg / [height in meters]^2) of 24 based on a height of 162cm and a weight of 63kg, who worked three of the four quarters in the year before giving birth, has four siblings, has the mean AFQT score of other twenty-three-year-old women in the NLSY, was on-time in school (within one grade) in an urban household with an employed male at age 14, whose mother (the maternal grandmother) completed twelve years of education and the prices for cigarette, alcohol, medical services and food are at the 1984 level. Our reference mother is someone for whom we expect favorable birth outcomes. We put great effort into eliciting prior beliefs about such a mother.

3. Modeling

3.1 Modeling Strategy

Our distribution of interest, for singleton first-born live births, is the joint distribution of four birth inputs (S, D, PC, and WG) and three birth outputs (G, BL, and BW), given the exogenous variables x. We choose a fairly large 155-dimensional parametric window to model this seven-dimensional conditional distribution of endogenous variables z.

A priority for us is addressing simultaneity of the seven variables in z. When simultaneity issues are ignored, questions regarding the effects on endogenous variables z of changing exogenous variables x, assume an unresponsive mother who does not respond intelligently to changes in her environment. For example, suppose a component in x measures access to prenatal care. The meaningful answer to what is the effect on BW of changing this access should allow the mother to adjust the prenatal care she employs. The standard BW regression, which contains measures of both prenatal care and access variables, is ***not*** designed to answer such a question.

While we draw upon the economics literature, we do ***not*** invoke a formal optimization approach. We specify reduced forms for the four inputs, and then a triangular specification in which G depends on the four inputs, and BL, BW together have a bivariate relationship depending on the four inputs and G. Our model is over-identified and yields a fairly simple specification for all three output equations. In our preferred maintained specification H_* the three output equations are distinguishable (i.e., identified) by 54 exclusion restrictions on coefficients of x_7 - x_{25} in the G, BL, and BW equations. The three output equations are identified by zero restrictions on maternal weight (x_6) in the BL equation, and on maternal height (x_5) in the BW equation.

Following the strategy outlined in Poirier (1995, Chapter 10), we choose our initial window in anticipation that a larger, more complicated one is ***not*** required. Of course there are many ways we could expand our initial window. One obvious way is to test some of the overidentifying restrictions that are a prerequisite for interpreting our model structurally. Specifically, we permit the 18

coefficients of x_7 - x_{12} in the G, BL, and BW equations to be nonzero under the alternative specification H_A. If our birth outcome production function reflects a biological transformation from birth inputs into birth outputs, then it should remain invariant over time and not differ according to mothers' geographical region, AFQT score, or family income. Our prior in Section 3.3 reflects this viewpoint. In Section 4.3 we test these 18 overidentifying restrictions.

3.2 An Econometric Window

Consider a sample of T independent singleton first-born live births indexed by the subscript i. Let $[S_i^*, D_i^*, PC_i^*]'$ (i = 1, 2, ..., T) denote latent variables underlying the binary birth inputs $[S_i, D_i, PC_i]' = [\mathbf{1}(S_i^*), \mathbf{1}(D_i^*), \mathbf{1}(PC_i^*)]'$ (i = 1, 2, ..., T), where $\mathbf{1}(\bullet)$ denotes an indicator function which equals unity if the argument is positive and equals zero otherwise. We partition the endogenous variables into inputs z_{i1} and outputs z_{i2}: $z_{i1}^* = [S_i^*, D_i^*, PC_i^*, WG_i]'$, $z_{i1} = [S_i, D_i, PC_i, WG_i]'$, $z_{i2} = [G_i, BL_i, BW_i]'$ (i = 1, 2, ..., T). Let x_i (i = 1, 2, ..., T) denote K×1 vectors of exogenous variables.

Suppose the four inputs are generated from the following specification

$$z_{i1}^* = \Delta_1' x_i + \varepsilon_{i1}, \tag{1}$$

where $\Delta_1 = [\Delta_S, \Delta_D, \Delta_{PC}, \Delta_{WG}]$ is K×4. Also suppose the three birth outputs are related to $z_{i1} = [S_i, D_i, PC_i, WG_i]'$ as follows:

$$z_{i2}'\Gamma_2 = z_{i1}'\Gamma_1 + x_i'\Delta_2 + \varepsilon_{i2}', \tag{2}$$

where $\varepsilon_i = [\varepsilon_{i1}, \varepsilon_{i2}]' \,|\, x_i \sim$ i.i.d. $N_7(0_7, \Sigma)$ (i = 1, 2, ..., T), Γ_2 is nonsingular,

$$\Gamma_1 = \begin{bmatrix} \gamma_{S,G} & \gamma_{S,BL} & \gamma_{S,BW} \\ \gamma_{D,G} & \gamma_{D,BL} & \gamma_{D,BW} \\ \gamma_{PC,G} & \gamma_{PC,BL} & \gamma_{PC,BW} \\ \gamma_{WG,G} & \gamma_{WG,BL} & \gamma_{WG,BW} \end{bmatrix} = \left[\gamma_G \mid \gamma_{BL} \mid \gamma_{BW}\right], \tag{3}$$

where $\Delta_{*,j} = [\delta_{7,j}, \ldots, \delta_{12,j}]'$, (j = G, BL, BW), and

The coefficients in $\Delta_{*,j}$ (j = G, BL, BW) are set to zero under our maintained specification. For added

$$\Gamma_2 = \begin{bmatrix} 1 & -\gamma_{G,BL} & -\gamma_{G,BW} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{4}$$

$$\Delta_2 = \begin{bmatrix} \delta_G & \delta_{BL} & \delta_{BW} \\ \delta_{5,G} & \delta_{5,BL} & 0 \\ \delta_{6,G} & 0 & \delta_{6,BW} \\ \Delta_{*,G} & \Delta_{*,BL} & \Delta_{*,BW} \\ 0_{13} & 0_{13} & 0_{13} \end{bmatrix}, \tag{5}$$

$$\Sigma = \left[\begin{array}{cccc|ccc} 1 & \sigma_{S,D} & \sigma_{S,PC} & \sigma_{S,WG} & \sigma_{S,G} & \sigma_{S,BL} & \sigma_{S,BW} \\ \sigma_{S,D} & 1 & \sigma_{D,PC} & \sigma_{D,WG} & \sigma_{D,G} & \sigma_{D,BL} & \sigma_{D,BW} \\ \sigma_{S,PC} & \sigma_{D,WG} & 1 & \sigma_{PC,WG} & \sigma_{PC,G} & \sigma_{PC,BL} & \sigma_{PC,BW} \\ \sigma_{S,WG} & \sigma_{D,WG} & \sigma_{PC,WG} & \sigma^2_{WG} & \sigma_{WG,G} & \sigma_{WG,BL} & \sigma_{WG,BW} \\ \hline \sigma_{S,G} & \sigma_{D,G} & \sigma_{PC,G} & \sigma_{WG,G} & \sigma^2_{G} & \sigma_{G,BL} & \sigma_{G,BW} \\ \sigma_{S,BL} & \sigma_{D,BL} & \sigma_{PC,BL} & \sigma_{WG,BL} & \sigma_{G,BL} & \sigma^2_{BL} & \sigma_{BL,BW} \\ \sigma_{S,BW} & \sigma_{D,BW} & \sigma_{PC,BW} & \sigma_{WG,BW} & \sigma_{G,BW} & \sigma_{BL,BW} & \sigma^2_{BW} \end{array}\right] = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}' & \Sigma_{22} \end{bmatrix}. \tag{6}$$

clarity, we let $x_i^{\star} = [1, x_{i2}, x_{i3}, x_{i4}]'$ and write out the transpose of output equations in (2):

$$G_i = z_{i1}'\gamma_G + x_i^{\bigstar\prime}\delta_G + x_{i5}\delta_{5,G} + x_{i6}\delta_{6,G} + \varepsilon_{i,G},$$

$$BL_i = G_i\gamma_{G,BL} + z_{i1}'\gamma_{BL} + x_i^{\bigstar\prime}\delta_{BL} + x_{i5}\delta_{5,BL} + \varepsilon_{i,BL},$$

$$BW_i = G_i\gamma_{G,BW} + z_{i1}'\gamma_{BW} + x_i^{\bigstar\prime}\delta_{BW} + x_{i6}\delta_{6,BW} + \varepsilon_{i,BW}.$$

The specification in (1) - (6) warrants a few comments. It reflects a view of the world in which reduced form (1) is postulated for the four inputs (S, D, PC, and WG), and then a ***triangular view*** (2) and (4) of the three outputs (G, BL, and BW) is postulated in which G is determined based on the four inputs, and then BL and BW are jointly determined as functions of the four inputs and G. The model is not recursive because Σ is permitted to be non-diagonal. The model is nonlinear because of the jointly determined dummy endogenous variables (S, D, and PC). The specification of numerous zero restrictions on Δ_2 in (5) ensures that the order condition for identification is satisfied.

Let θ denote the unique unknown elements in Γ_1, Γ_2, Δ, and Σ. Also let Θ denote the permissible parameter space. Appendix A.1 contains the derivation of the joint density for the four observed inputs and three outputs of our BPF. The resulting likelihood function, $\mathfrak{L}(\theta; Z, X)$, is given by (A.12).

3.3 Our Family of Prior Distributions

We strive to provide a ***public prior*** which captures other researchers' interests and permits them to reweight our Markov chain Monte Carlo (MCMC) simulations to obtain results corresponding to more tightly articulated prior beliefs [Geweke (1999)]. For researchers who are interested in reweighting using their own priors, our posterior simulation results can be downloaded at ***http://finance.commerce.ubc.ca/research/abstracts/UBCFIN00-3.html***. Our prior is proper, but moderately diffuse. We use the same prior for all groups. Our reading of the existing literature

suggests the following broad properties will capture a bevy of researchers' professional opinions as well as ours.

The vast majority of studies on BW, particularly in the biomedical literature, are single-equation models that ignore simultaneity issues [a notable exception is Permutt and Hebel (1989)]. To reflect this fact we center our prior for Σ over a diagonal matrix.

Regarding the effects of birth inputs on birth outputs, there is substantial professional support that smoking has negative consequences on birth outputs, particularly on G and BW [Shiono and Behrman (1995)]. The effect of moderate drinking on birth outputs is less clear and may even be positive. The effect of PC on birth outputs is even less obvious due to sample selection effects [Shiono and Behrman (1995)], but we believe PC may be helpful for BW. We also believe WG and G have positive effects on BL and BW. Our beliefs on the effects of remaining endogenous input variables on endogenous output variables are fairly diffuse and centered over zero.

Among exogenous variables, we believe, *ceteris paribus*, male infants are slightly longer and heavier than females; calender time has a slightly negative effect on smoking and drinking, a slightly positive effect on PC, and a very uncertain positive effect on WG. AFQT has a moderately negative effect on the probability of smoking and drinking, and a moderately positive effect on PC and WG. The grandmother's education has a slightly negative effect on smoking and drinking, and a positive effect on PC and WG. Finally, not on time in school at age 14 has a positive effect on smoking and drinking, and a negative effect on PC and WG. The effects of all other exogenous variables on the remaining endogenous variables are centered over zero with fairly large standard deviations.

These general beliefs serve as guidelines for choosing a family of priors. We restrict our sensitivity analysis to the priors on Γ_1, Γ_2, and Δ. We select normal prior distributions for all parameters except the variances of the four continuous endogenous variables which are assigned

$$s_2 = [\sigma_{S,WG}, \sigma_{S,G}, \sigma_{S,BL}, \sigma_{S,BW}, \sigma_{D,WG}, \sigma_{D,G}]', \quad (8)$$

$$s_3 = [\sigma_{D,BL}, \sigma_{D,BW}, \sigma_{PC,WG}, \sigma_{PC,G}, \sigma_{PC,BL}, \sigma_{PC,BW}]', \quad (9)$$

$$s_4 = [\sigma_{WG,G}, \sigma_{WG,BL}, \sigma_{WG,BW}, \sigma_{G,BL}, \sigma_{G,BW}, \sigma_{BL,BW}]', \quad (10)$$

$$s_5 = \sigma^2_{WG}, \quad s_6 = \sigma^2_{G}, \quad s_7 = \sigma^2_{BL}, \quad s_8 = \sigma^2_{BW}. \quad (11)$$

independent inverse gamma distributions. These normal priors are independent except for regional effects and elements of Σ which are tied together through the positive definiteness of Σ.

Due to the presence of three probit regressions in our system, the standard Wishart prior on the inverse of Σ is not appropriate and the natural conjugacy between the prior and likelihood breaks down. Our prior beliefs regarding Σ are summarized in Table 3. Beliefs about across-equation covariances are all centered over zero which favors using single-equation techniques. Beliefs about the variances of WG, G, BL, and BW are represented by fairly diffuse (but proper) inverted gamma distributions with means and standard deviations given in Table 3.

We partition the 25 unknown elements of Σ into eight blocks:

$$s_1 = [\sigma_{S,D}, \sigma_{S,PC}, \sigma_{D,PC}]', \quad (7)$$

The joint prior specification for the eight blocks is [using the notation of Poirier (1995, p. 111, (e)]:

$$f(\Sigma) = \varphi_3(s_1 \mid 0, 1)\left[\prod_{j=2}^{4} \varphi_6(s_j \mid 0_6, 9I_6)\right] f_{IG}(s_5 \mid 2.5, .01)\, f_{IG}(s_6 \mid 2.5, .08)\, f_{IG}(s_7 \mid 2.5, .08)\, f_{IG}(s_8 \mid 2.5, 2), \quad (12)$$

subject to the constraints that elements of s_1 are in the interval [-1, 1], and the resulting variance-

covariance matrix is positive definite.

The 130-dimensional prior for β defined by (A.4) and (A.6), which consists of elements from Γ_1, Γ_2, and Δ, is parameterized in terms of three hyperparameters (ξ, ω_1 , and ω_2) that control the tightness of the prior. We assign these hyperparameters default values and change them to see if results change substantially. Our ***default prior specification*** is $\xi = 1$, $\omega_1 = .1936$, $\omega_2 = 9$. We divide these default values by four to obtain the ***tight prior specification*** $\xi = .25$, $\omega_1 = .0484$, $\omega_2 = 2.25$, and we multiply them by two to obtain the ***loose prior specification*** $\xi = 2$, $\omega_1 = .3872$, $\omega_2 = 18$.

For the unknown elements of Γ_1 in (3) and of Γ_2 in (4), we assume independent univariate normal priors with means and standard deviations given in Table 4, where ξ controls prior variances. Under H_A , for the unknown elements in Δ, we also assume normal priors with means and standard deviations given in Table 5, where ω_1 and ω_2 control prior variances. The prior under H_* is taken to be the same as in Table 5 except that the elements in Δ_{j*} are dogmatically set equal to zero. The components of these distributions are all independent except for the regional effects, which we assume are exchangeable and assigned a common covariance ω_1.

The exogenous variables x_7 , ..., x_{25} are instruments in subsequent birth output equations where they are subject to dogmatic zero restrictions satisfying the order condition for over-identification. Our priors reflect this instrument role. The nonzero prior means (-.2, -1, -.5, and .6; or .2, .1, .5, and -.6) for the coefficients of $x_{10,\,j}$, $x_{11,\,j}$, $x_{18,\,j}$, and $x_{19,j}$ imply substantial mass away from the point 0_4 which fails the rank condition. The other variables among x_7 - x_{25} also serve as instruments in subsequent birth output equations, but we are less certain of their reliability as instruments, and so their prior means of zero fail the rank condition.

As discussed in Section 3.1, we choose a highly over-identified specification for our maintained hypothesis H_*, and a less restricted specification H_A as an alternative hypothesis that we

expect will not lead to rejecting H_*. Under both H_* and H_A, our priors for all other parameters are the same. Given our 155-dimensional window there are ample opportunities for pretesting, but we do not engage in it (exceptions are the diagnostic testing of H_* and the pooling of samples). Instead we report posterior means and standard deviations. To give a quick, visual indication of the posterior mass around the means, we indicate the relative size of the posterior mean to the posterior standard deviation by the border of the table cell as described in Table 6. While such crude measures may serve to indicate whether interval estimates include points such as the origin, we do not intend for them to be tests of sharp hypotheses. Our priors do not allocate point masses at zero for coefficients other than $\Delta_{*,\,j}$ (j = G, BL, BW). If they did and if we wanted to test the sharp hypotheses, then we could calculate the appropriate Bayes factor.

4. Empirical Results

4.1 Introductory Comments

Because all our priors are proper, we can compute the marginal data density under each prior for both specifications. Thus, not only can we compare posterior means and standard deviations of parameters and predictions across priors and specifications, we can also assess which prior the data favor. It turns out that the data never favor the loose prior for any of our groups, and almost always mildly favor our tight prior over our default choice. We do not intend to "test" our default prior. Rather we report results for the posterior corresponding to the default prior specification $\xi = 1$, $\omega_1 = .1936$, $\omega_2 = 9$, and discuss interesting departures where appropriate. These departures always involve the posterior corresponding to the tight prior because the data favor the tight specification. We emphasize the default prior because we think its relative looseness will appeal to a wider audience.

4.2 Pooling of Groups

Formal comparison of our model across the Main and the Supplemental samples for Blacks

and Hispanics yields logarithmic Bayes factors favoring pooling ranging from 159 to 347 [Li and Poirier (2000, Table 9)] across the three priors and two model specifications. This confirms our prior beliefs, and so all results are presented in terms of pooled Black and pooled Hispanic samples.

The literature is filled with attempts to account for the differences in the marginal distributions of birth outcomes like BW across racial/ethnic groups. We begin our analyses with a common window and prior, but we deal with each group separately. As we progressively pool the groups, the logarithmic Bayes factors favoring pooling range from 183 to 950 under the preferred specification, and from 221 to 874 under the alternative specification. We have investigated many different poolings of groups and in all instances the data favor pooling. We present results for our preferred case in which all five groups are pooled, and four group dummies are entered into all seven birth equations. We center our prior beliefs on all group dummies over zero and choose prior variances equal to those of other binary variables in each equation as shown in Table 5. Jointly testing that all $28 = 4\times7$ coefficients are zero yields the logarithmic Bayes factors in favor of pooling under our default prior of 628 under H_* and 1,702 under H_A.

Despite these strong indications for pooling, our prior probability of finding a window free of any group-specific factors is sufficiently low that we choose the less extreme specification in which the 28 dummies are included. Another reason for doing so (from an estimation standpoint), is that the posterior mean Main White-Black differential is often many times its posterior standard deviation. The separate results for each group involve a $4\times155 + 151 = 771$ dimensional view of the world. The pooled results in this section reduce it to a 183-dimensional view.

4.3 Evidence of Structure

We investigate whether our output equations reflects a biological structure in three related ways. For brevity, we report results only for our default prior. Firstly, the logarithmic Bayes factor

in favor of our maintained specification H_*: $\Delta_{*,G} = \Delta_{*,BL} = \Delta_{*,BW} = 0_6$ versus the alternative H_A: $\Delta_{*,G} \neq 0_6$ or $\Delta_{*,BL} \neq 0_6$ or $\Delta_{*,BW} \neq 0_6$ is overwhelming: 1,107. Secondly, the predictive densities for all endogenous variables for our reference mother in each group differ little across H_* and H_A, and across prior specifications (Table 7). Thirdly, under H_A the six additional variables x_7 - x_{12} add relatively little to the three output equations. Table 8 contains the posterior means and standard deviations of the coefficients of these variables and the group dummies. Because of these results, ***subsequent results are conditioned upon H_*.*** Complete results under the H_A are available from the authors upon request.

4.4 System Results

Our treatment of simultaneity, in contrast to the biomedical literature, is a distinguishing feature of our model. While our window imposes triangularity, it does not impose a full recursive specification. The posterior results provide strong support for the model not being fully recursive.

Although our prior for Σ is centered over a diagonal matrix (supporting the use of single-equation methods), the need for simultaneous equations techniques is apparent in our posterior results in Table 9. Briefly, the connection between the unexplained parts of our seven endogenous variables is as follows. There is evidence of strong correlation between S* and D*, little correlation between PC*, S*, and D*, and small in absolute value (but greater than posterior standard deviations) correlations between WG and all other inputs. All three birth outputs exhibit substantial positive correlations among themselves which are large in size and relative to their standard deviations. Of particular interest is the off-diagonal block of correlations between inputs and outputs. G has noticeable correlation with all birth inputs, BL only with PC* where it is negative, and BW with S* and PC*. WG has surprisingly small correlation with birth outputs.

4.5 Input Equations

Our interest in the parameters of the input equations is minimal compared to the output equations, and so we devote less attention to them. Table 10 contains the posterior and prior means and standard deviations for the elements of Δ_1 under our default prior. The price indices are not good instruments in any of the input equations. But most other variables among x_7 - x_{25} have substantial posterior mass away from zero in some equations suggesting they satisfy at least one requirement of a legitimate instrumental variable for the output equations. Finally, we note that our loose and tight priors yield qualitatively similar results for the input equations. Complete results are available from the authors upon request.

4.6 Output Equations

The output equations are of prime importance. They describe how birth inputs together with the biological size of the mother are transformed into birth outputs describing the physical characteristics of the infant.

Table 11 contains the posterior birth output results. The effect of smoking appears negative in all output equations, and particularly so in the BW equation where smoking translates into an expected BW reduction of .4016kg. PC has a consistent sizeable positive effect on all birth outputs. Obtaining prenatal care in the first trimester translates into an increase of 2.356 weeks in gestation, 2.186cm in BL, and .5051kg in BW. D has a mixed effect across outputs, but is noticeably negative for G where its posterior mean effect is to reduce gestational age by 1.238 weeks. Maternal nutrition has a positive effect in all birth output equations and is sizeable for BL. G has the expected positive effects on BL and BW, but their size is not large. Maternal size has reasonable positive effects on all birth outputs although the posterior mean effects are not large. The posterior mean effect of a male infant on BL is .7886cm and on BW is .0958kg. The posterior mean effects of maternal age are negative (but small) on all birth outputs.

Regarding the group effects, relative to the Main White group the picture that emerges from Tables 10 and 11 is as follows. The posterior mean of the Black effect is consistently negative and more than twice its posterior standard deviation in all equations except the PC equation. Similarly, the Hispanic effect is negative (except in the WG equation) and usually not as large as the Black effect in absolute value nor relative to its posterior standard deviation. The posterior mean of the Supplemental White effect is positive in the input equations and negative in the output equations, but not large relative to its posterior standard deviation. Finally, the posterior means of the Native American effect are of mixed signs and small in absolute values and relative to their posterior standard deviations.

In summary, our analysis of group differences is as follows. If prior beliefs are centered over zero for group effects, then the Bayes factors suggest pooling. This "testing" conclusion is contrasted in our estimation results largely due to the Black and to a lesser degree Hispanic differences from the Main White group. Our results suggest that birth outcomes on average are similar for Main Whites and Native Americans, slightly better than for Supplemental Whites, noticeably better than for Hispanics, and substantially better than for Blacks. Even after controlling for all the exogenous variables in the model, the posterior mean difference between Blacks and Main Whites is -.5038 weeks for gestational age, -.7762cm for BL, and -.2072kg for BW. Furthermore, these effects are all more than twice their posterior standard deviations.

4.7 Prediction

Given out-of-sample values of $\tilde{x}$, the predictive density for the out-of-sample of

$\tilde{z}^{*} = [\tilde{z}_1^{*}, \tilde{z}_2]' = [\tilde{S}^{*}, \tilde{D}^{*}, \tilde{PC}^{*}, \tilde{WG}, \tilde{G}, \tilde{BL}, \tilde{BW}]'$ is

$$
\begin{aligned}
f(\tilde{z}_1^*, \tilde{z}_2 \mid \tilde{x}, Z, X) &= \int_{\Theta} f(\tilde{z}_1^*, \tilde{z}_2 \mid \theta)\, f(\theta \mid Z, X)\, d\theta \\
&= \int_{\Theta} \varphi_4(\tilde{z}_1^* \mid \Delta_1' \tilde{x}, \Sigma_{11})\, \varphi_3(\tilde{z}_2 \mid \tilde{\mu}_2 + \Sigma_{12}' \Sigma_{11}^{-1} (\tilde{z}_1^* - \Delta_1' \tilde{x}), \Sigma_{2|1})\, f(\theta \mid Z, X)\, d\theta,
\end{aligned} \tag{13}
$$

where $\tilde{\mu}_2 = \tilde{\mu}_2(\tilde{z}_1, \tilde{G}, \tilde{x}, \beta) = \tilde{W}_2 \beta$, $\Sigma_{2|1} = \Sigma_{22} - \Sigma_{12}' \Sigma_{11}^{-1} \Sigma_{12}$, and

$$
\tilde{W}_2 = \begin{bmatrix}
\tilde{z}_1' & \tilde{x}^{\star\prime} & \tilde{x}_5 & \tilde{x}_6 & 0 & 0_4' & 0_4' & 0 & 0 & 0_4' & 0_4' & 0 \\
0_4' & 0_4' & 0 & 0 & \tilde{G} & \tilde{z}_1' & \tilde{x}^{\star\prime} & \tilde{x}_5 & 0 & 0_4' & 0_4' & 0 \\
0_4' & 0_4' & 0 & 0 & 0 & 0_4' & 0_4' & 0 & \tilde{G} & \tilde{z}_1' & \tilde{x}^{\star\prime} & \tilde{x}_6
\end{bmatrix}, \tag{14}
$$

with $\tilde{x}_i^{\star} = [\tilde{x}_{i1}, \tilde{x}_{i2}, \tilde{x}_{i3}, \tilde{x}_{i4}]$, and $\tilde{z}_1 = [\tilde{S}, \tilde{D}, \tilde{PC}, \tilde{WG}]' = [\mathbf{1}(\tilde{z}_1^*), \mathbf{1}(\tilde{z}_2^*), \mathbf{1}(\tilde{z}_3^*), \tilde{WG}]'$. The predictive distribution for birth outputs, obtained from (13) by integrating out the inputs is:

$$
\begin{aligned}
f(\tilde{z}_2 \mid \tilde{x}, Z, X) &= \int_{\Theta} \left[\int_{\Re^4} f(\tilde{z}_1^*, \tilde{z}_2 \mid \theta)\, d\tilde{z}_1^* \right] f(\theta \mid Z, X)\, d\theta \\
&= \int_{\Theta} \left[\int_{\Re^4} \varphi_4(\tilde{z}_1^* \mid \Delta_1' \tilde{x}, \Sigma_{11})\, \varphi_3(\tilde{z}_2 \mid \tilde{\mu}_2 + \Sigma_{12}' \Sigma_{11}^{-1} [\tilde{z}_1^* - \Delta_1' \tilde{x}], \Sigma_{2|1})\, d\tilde{z}_1^* \right] f(\theta \mid Z, X)\, d\theta \\
&= \mathrm{E}_{\theta \mid X, Z} \left[\mathrm{E}_{\tilde{z}_1^* \mid \tilde{x}, \theta} \left(\varphi_3(\tilde{z}_2 \mid \tilde{\mu}_2 + \Sigma_{12}' \Sigma_{11}^{-1} [\tilde{z}_1^* - \Delta_1' \tilde{x}], \Sigma_{2|1}) \right) \right].
\end{aligned} \tag{15}
$$

Corresponding to our reference mother, the univariate predictive output densities shown in Figures 4-6 (for G, BL, and BW, respectively) can be derived from (15). These figures depict the univariate predictive output densities for each group and the very diffuse prior predictive density embodying only the informative prior and no data.

4.8 High/Low Risk Birth Weight Puzzle

In this section we investigate the High/Low Risk Birth Weight Puzzle mentioned in Section 1.3 and its applicability to other groups as well as Blacks versus Whites. Figure 7 provides the predictive distributions of BW for the five groups when evaluated for a mother characterized by different risk levels. The different risk levels correspond to shifting particular exogenous variables from their zero values for the reference mother in Figure 6 to the following new values for very high risk (VHR), high risk (HR), low risk (LR), and very low risk (VLR) mothers, respectively:

$$x_{11}^{VHR} = -1.2556,\ x_{12}^{VHR} = -20,\ x_{13}^{VHR} = 1,\ x_{15}^{VHR} = -2,\ x_{17}^{VHR} = 2,\ x_{18}^{VHR} = -4,\ x_{19}^{VHR} = 1,\ x_{21}^{VHR} = 1,$$

$$x_{11}^{HR} = -.6278,\ x_{12}^{HR} = -10,\ x_{13}^{HR} = 1,\ x_{15}^{HR} = -1,\ x_{17}^{HR} = 1,\ x_{18}^{HR} = -2,\ x_{19}^{HR} = 1,\ x_{21}^{HR} = 1,$$

$$x_{11}^{LR} = .6278,\ x_{12}^{LR} = 10,\ x_{15}^{LR} = 1,\ x_{17}^{LR} = -1,\ x_{18}^{LR} = 2,$$

$$x_{11}^{VLR} = 1.2556,\ x_{12}^{VLR} = 20,\ x_{15}^{VLR} = 2,\ x_{17}^{VLR} = -2,\ x_{18}^{VLR} = 4.$$

In other words, we define the various risk levels by moving AFQT score ±1 and ±2 Main White standard deviations (.6278), moving household income in one or two steps of ±$10,000, adding or subtracting one or two adults from the household and one or two maternal siblings, adding or subtracting two or four years to the grandmother's education, and turning on the binary indicators for not on time in school and no male present in the household at age 14. Table 12 gives predictive probabilities of VLBW and LBW, the predictive means of BW, and the predictive standard deviations in BW of the distributions shown in Figure 7. Table 12 confirms our expectation that these different assignments

of exogenous variables lead to improved BW outcomes moving from VHR to VLR values.

The High/Low Risk Birth Weight Puzzle is apparent for Blacks, Hispanics, and Native Americans. In all three cases, high-risk mothers are more comparable to high-risk Main Whites than low- risk mothers are to low-risk Main Whites. This can also be seen in Table 13 which expresses the ratio of the probability of LBW, the mean of BW, and the standard deviation in BW to their Main White counterparts. The puzzle is not evident for Supplemental Whites.

The interpretation of the puzzles is up for grabs. It seems to work through the following channels. Table 14 contains the predictive means of the four birth inputs and G corresponding to mothers of varying risk. Clearly, moving from VHR to VLR (left to right in Table 14) mothers smoke less (except for Hispanics), are more likely to seek prenatal care in the first trimester, and have better (except for Main and Supplemental Whites) maternal nutrition (i.e., increased WG). All of these behaviors contribute to higher BW (Table 11). Also, moving from VHR to VLR, mothers are more likely to drink, but this has relatively little impact on BW (Table 11). What hurts Hispanics is the increased probability of smoking when moving from VHR to VLR. For Blacks and Native Americans, gestational ages are lower as we move from VHR to VLR (although the changes are small), and this hurts BW (Table 11).

4.9 Convergence Diagnostics

We use a plot of all MCMC draws and the Convergence Diagnostic and Output Analysis (CODA) software [Cowles and Carlin (1996) for an introduction] to check for convergence. Results of the convergence diagnostics are available from the authors upon request.

5. Discussion

It is well acknowledged that BW is probably the single most important indicator of infant health. In this paper, we focus on explaining the birth outcomes such as gestation, BL, and BW using

a simultaneous equations approach. On the other hand, the more interesting and ultimately relevant question to ask, from a society viewpoint, is what factors affect children's attainment later in life. Our modeling framework turns out to be quite useful in answering questions like this. We conjecture that BW and related birth measurements are the intervening variables in explaining children's development later in life, and we plan to investigate further in future work.

Appendices

A.1 Likelihood Function

Let $\varphi_m(\bullet\,|\,\bullet,\bullet)$ denote an m-dimensional normal density with given mean vector and variance-covariance matrix. Because the density of ε_{i2} given ε_{i1} is $f(\varepsilon_{i2}|\varepsilon_{i1}, \Sigma) = \varphi_3(\varepsilon_{i2}|\Sigma_{12}'\Sigma_{11}^{-1}\varepsilon_{i1}, \Sigma_{2|1})$, where $\Sigma_{2|1} = \Sigma_{22} - \Sigma_{12}\Sigma_{11}^{-1}\Sigma_{12}$, it follows using change-of-variable techniques, and noting from (2) and (4) that the Jacobian of the transformation from ε_{i2} to z_{i2} is unity due to the triangularity of Γ_2, the distribution of the outputs z_{i2} given the inputs z_{i1}^* is

$$\begin{aligned} f(z_{i2}\,|\,z_{i1}^*, x_i, \theta) &= \varphi_3(\Gamma_2'z_{i2} - \Gamma_1'z_{i1} - \Delta_2'x_i\,|\,\Sigma_{12}'\Sigma_{11}^{-1}(z_{i1}^* - \Delta_1'x_i), \Sigma_{2|1}) \\ &= \varphi_3(z_{i2}\,|\,\mu_{i2} + \Sigma_{12}'\Sigma_{11}^{-1}(z_{i1}^* - \Delta_1'x_i), \Sigma_{2|1}), \end{aligned} \tag{A.1}$$

where under the maintained hypothesis H_*:

$$\begin{aligned} \mu_{i2} &= \mu_{i2}[z_{i1}, G_i, x_i, \theta] = \begin{bmatrix} 0 \\ \gamma_{G,BL}G_i \\ \gamma_{G,BW}G_i \end{bmatrix} + \Gamma_1'z_{i1} + \Delta_2'x_i \\ &= W_{i2}\beta_2, \end{aligned} \tag{A.2}$$

W_{i2} is the 3×30 matrix

$$W_{i2} = \begin{bmatrix} z_{i1}' & x_i^{\star\prime} & x_{i5} & x_{i6} & 0 & 0_4' & 0_4' & 0 & 0 & 0_4' & 0_4' & 0 \\ 0_4' & 0_4' & 0 & 0 & G_i & z_{i1}' & x_i^{\star\prime} & x_{i5} & 0 & 0_4' & 0_4' & 0 \\ 0_4' & 0_4' & 0 & 0 & 0 & 0_4' & 0_4 & 0 & G_i & z_{i1}' & x_i^{\star\prime} & x_{i6} \end{bmatrix}, \qquad \text{(A.3)}$$

$x_i^{\star} = [x_{i1}, x_{i2}, x_{i3}, x_{i4}]'$, and

$$\beta_2 = [\gamma_G', \delta_G', \delta_{5,G}, \delta_{6,G}, \gamma_{G,BL}, \gamma_{BL}', \delta_{BL}', \delta_{5,BL}, \gamma_{G,BW}, \gamma_{BW}', \delta_{BW}', \delta_{6,BW}]'. \qquad \text{(A.4)}$$

Combining conditional density (A.1) with the marginal density $\varphi_4(z_{i1}^* \mid \Delta_1' x_i, \Sigma_{11})$ of z_{i1}^*, and using

properties of the multivariate normal density, it follows that the joint density of z_{i1}^* and z_{i2} is

$$\begin{aligned} f(z_{i1}^*, z_{i2} \mid x_i, \theta) &= \varphi_4(z_{i1}^* \mid \Delta_1' x_i, \Sigma_{11})\, \varphi_3(z_{i2} \mid \mu_{i2} + \Sigma_{12}' \Sigma_{11}^{-1}(z_{i1}^* - \Delta_1' x_i), \Sigma_{2|1}) \\ &= \varphi_7\left(\begin{bmatrix} z_{i1}^* \\ z_{i2} \end{bmatrix} \mid \mu_i, \Sigma \right), \end{aligned} \qquad \text{(A.5)}$$

where $\mu_i = W_i \beta$,

$$\beta = [\beta_1', \beta_2']', \qquad \beta_1 = \text{vec}(\Delta_1), \qquad \text{(A.6)}$$

and

$$W_i = \begin{bmatrix} I_4 \otimes x_i' & 0_{4\times 30} \\ 0_{3\times 100} & W_{i2} \end{bmatrix} \qquad \text{(A.7)}$$

is 7×130. Note that (A.5) does ***not*** imply z_{i1}^* and z_{i2} are multivariate normal because μ_{i2} depends on elements in z_{i1}^* (through z_{i1}) and in z_{i2}. Under the alternative hypothesis H_A, 18 additional columns are added to W_{i2}, and $\Delta_{*,j}$ (j = G, BL, BW) are added to β_2.

Given the observed $[S_i, D_i, PC_i]'$, define the lower and upper integration limits

$$\underline{a}_{S_i} = \begin{Bmatrix} -\infty, & \text{if} \quad S_i = 0 \\ -x_i'\Delta_S, & \text{if} \quad S_i = 1 \end{Bmatrix}, \qquad \bar{a}_{S_i} = \begin{Bmatrix} -x_i'\Delta_S, & \text{if} \quad S_i = 0 \\ \infty, & \text{if} \quad S_i = 1 \end{Bmatrix}, \tag{A.8}$$

$$\underline{a}_{D_i} = \begin{Bmatrix} -\infty, & \text{if} \quad D_i = 0 \\ -x_i'\Delta_D, & \text{if} \quad D_i = 1 \end{Bmatrix}, \qquad \bar{a}_{D_i} = \begin{Bmatrix} -x_i'\Delta_D, & \text{if} \quad D_i = 0 \\ \infty, & \text{if} \quad D_i = 1 \end{Bmatrix}, \tag{A.9}$$

$$\underline{a}_{PC_i} = \begin{Bmatrix} -\infty, & \text{if} \quad PC_i = 0 \\ -x_i'\Delta_{PC}, & \text{if} \quad PC_i = 1 \end{Bmatrix}, \qquad \bar{a}_{PC_i} = \begin{Bmatrix} -x_i'\Delta_{PC}, & \text{if} \quad PC_i = 0 \\ \infty, & \text{if} \quad PC_i = 1 \end{Bmatrix}. \tag{A.10}$$

Then the joint density for all seven observed endogenous variables is

$$\begin{aligned} f(z_{i1}, z_{i2} \mid x_i, \theta) &= \int_{\underline{a}_{S_i}}^{\bar{a}_{S_i}} \int_{\underline{a}_{D_i}}^{\bar{a}_{D_i}} \int_{\underline{a}_{PC_i}}^{\bar{a}_{PC_i}} f(z_{i1}^*, z_{i2} \mid x_i, \theta)\, dPC_i^* dD_i^* dS_i^* \\ &= \int_{\underline{a}_{S_i}}^{\bar{a}_{S_i}} \int_{\underline{a}_{D_i}}^{\bar{a}_{D_i}} \int_{\underline{a}_{PC_i}}^{\bar{a}_{PC_i}} \varphi_4(z_{i1}^* \mid \Delta_1' x_i, \Sigma_{11})\, \varphi_3(z_{i2} \mid \mu_{i2} + \Sigma_{12}'\Sigma_{11}^{-1}(z_{i1}^* - \Delta_1' x_i), \Sigma_{2|1}))\, dPC_i^*\, dD_i^*\, dS_i^*. \end{aligned} \tag{A.11}$$

Stack observations to obtain the data matrices: $Z_1^* = [z_{11}^*, z_{21}^*, ..., z_{T1}^*]'$, $Z_1 = [z_{11}, z_{21}, ..., z_{T1}]'$, $Z_2 = [z_{12}, z_{22}, ..., z_{T2}]'$, $Z = [Z_1, Z_2]'$, and $X = [x_1, x_2, ..., x_T]'$. Assuming independent sampling, we choose to view the observed data, under H_*, through a 130 + 25 (unknown elements in Σ) = 155-dimensional parametric window given by the likelihood function

$$\mathcal{L}(\theta; Z, X) = \prod_{i=1}^{T} f(z_{i1}, z_{i2} \mid x_i, \theta). \qquad \text{(A.12)}$$

Given z estimation and testing in this framework is well developed in both classical and Bayesian literatures. The observability of only discretized versions of the endogenous variables in z_1, introduces some complications, but these can be overcome, as can any other nonlinearities in specification of the structural equations [Li (1998) and the references cited therein].

A.2 Computation

Given the triangular structure of our model, our posterior analysis proceeds in the following ways. Since there are three probit equations, it is computationally intensive to evaluate likelihood function (A.12) due to the trivariate integral required for each observation. The posterior density of the parameters $\theta = [\beta', \text{vech}(\Sigma)']'$ satisfies

$$f(\beta, \Sigma \mid Z, X) \sim f(\beta, \Sigma)\mathcal{L}(\beta, \Sigma; Z, X), \quad \text{for} \quad \Sigma \in C, \qquad \text{(A.13)}$$

where C is the region in which the variance-covariance matrix Σ is positive definite.

We employ a Bayesian approach for estimating simultaneous equations models with multiple probit regressions [similar to Chib and Greenberg (1998)]. We employ ***data augmentation*** to augment the observed data in order to simplify the posterior analysis. Specifically, we will obtain the joint posterior distribution of both the parameters and the latent data Y_1^* conditional on the observed data. According to Bayes theorem, this augmented posterior is

$$f(\beta, \Sigma, Y_1^* \mid Z, X) \propto f(\beta, \Sigma) f(Y_1^* \mid \beta, \Sigma, Z, X) \mathcal{L}(\beta, \Sigma; Z, X). \qquad \text{(A.14)}$$

Hence, the new posterior can be written as the product of the prior for the unknown parameters θ and

the ***augmented likelihood function*** $\mathfrak{L}^*(\beta, \Sigma; Z, X) = f(Y_1^* | \beta, \Sigma, Z, X)\, \mathfrak{L}(\beta, \Sigma; Z, X)$ based on both the latent dependent variables Y_1^* and the observed dependent variables Z. The former is the products of multivariate normal distributions, in which evaluation of high dimension integrals is not required.

Once the data is augmented, the posterior analysis of our simultaneous equations model with multiple probits is greatly simplified. Our Markov chain sampling scheme is constructed by iterating through the three distributions with densities: $f(Y_1^* | \beta, \Sigma, Z, X)$, $f(\beta | \Sigma, Y_1^*, Z, X)$, and $f(\Sigma | \beta, Y_1^*, Z, X)$. Each of these distributions can be sampled either directly or by Markov chain methods.

We begin with sampling the latent data Y_1^* from the conditional distribution $\mathbf{Y_1^* | \beta, \Sigma, Z, X}$. This is a multivariate normal density truncated to the region associated with the observed $Y_1 = (S, D, PC)$. For instance, if $[S_i, D_i, PC_i]' = [1, 1, 1]'$, then the normal distribution is truncated to the positive orthant. To sample this distribution, we can first obtain univariate conditional normals derived from the joint distribution and then apply the method developed in Geweke (1991) to generate univariate truncated normals through the components.

To describe the sampling scheme for the unknown parameters, we rewrite the augmented simultaneous equations model as

$$z = W\beta + \varepsilon, \qquad \text{(A.15)}$$

where $z = \text{vec}([Z_1^*, Z_2])$ and $\varepsilon \sim N_{7T}(0_{7T}, \Sigma \otimes I_T)$. Assuming prior independence between the regression parameter vector β and the variance-covariance matrix Σ, and we adopt the prior outlined in Section 3.3. Order the elements of β as indicated in (A.4) and (A.6), and similarly construct its prior mean $\underline{b}$ and variance-covariance matrix $\underline{Q}$ according to Tables 3-5. Then $\beta \sim N_{130}(\underline{b}, \underline{Q})$. By combining this prior for β with the augmented likelihood function, and noting that the two quadratic forms are linear in β given $W = W(Y_1^*, Z)$, we obtain the standard linear regression result

$$f(\beta \mid \Sigma, Y_1^*, Z, X) = \varphi_{130}(\beta \mid \bar{b}, \bar{Q}), \tag{A.16}$$

where

$$\bar{Q} = [\underline{Q}^{-1} + W'(\Sigma^{-1} \otimes I_T)W]^{-1}, \tag{A.17}$$

$$\bar{b} = \bar{Q}[\underline{Q}^{-1}\underline{b} + W'(\Sigma^{-1} \otimes I_T)z]. \tag{A.18}$$

Simulation from $\boldsymbol{\beta \mid \Sigma, Y_1^*, Z, X}$ is straightforward using (A.16).

Finally, we consider the sampling of the variance-covariance matrix Σ from $\boldsymbol{\Sigma \mid \beta, Y_1^*, Z, X}$. We sample the elements of the variance-covariance matrix Σ using the Metropolis-Hastings algorithm [Chib and Greenberg (1995) for an overview]. Let $q(\Sigma, \Sigma^\dagger \mid \beta, Y_1^*, Z, X)$ denote a proposal density that generates candidate draw $\Sigma^\dagger$ given the current value Σ. The choice of the proposal density is given later. The Metropolis-Hastings algorithm works in the following two steps.

(i) Sample a draw $\Sigma^\dagger$ given Σ from the proposal density $q(\Sigma, \Sigma^\dagger \mid \beta, Y_1^*, Z, X)$.

(ii) Move to $\Sigma^\dagger$ with probability

$$p(\Sigma, \Sigma^\dagger) = \min\left(\frac{f(\Sigma^\dagger) f(Y_1^* \mid \beta, \Sigma^\dagger, Z, X) \wp(\beta, \Sigma^\dagger; Z, X) \mathbf{1}(\Sigma^\dagger \in C)/q(\Sigma, \Sigma^\dagger \mid \beta, Y_1^*, Z, X)}{f(\Sigma) f(Y_1^* \mid \beta, \Sigma, Z, X) \wp(\beta, \Sigma; Z, X) \mathbf{1}(\Sigma \in C)/q(\Sigma^\dagger, \Sigma \mid \beta, Y_1^*, Z, X)}, 1 \right), \tag{A.19}$$

and stay at Σ with probability $1 - p(\Sigma, \Sigma^\dagger)$. Note that $\mathbf{1}(\Sigma^\dagger \in C)$ is an indicator function which equals unity if $\Sigma^\dagger$ is positive definite and equals zero otherwise.

Given the 25 unknown elements in Σ, it can be a challenging task to search for a suitable candidate-generating density. Therefore, we apply the Metropolis-Hastings algorithm in sequence

through these eight blocks defined in (7) - (11). We adopt the random walk chain to generate proposal values for the elements of the variance-covariance matrix. In particular, we use a multivariate normal candidate-generating density (draws outside the support C are discarded) for the first four blocks s_j (j = 1, 2, 3, 4) and a univariate normal density for the four diagonal elements s_j (j = 5, 6, 7, 8) (draws outside the support C are also discarded). The mean of the normal is given by the previous draw and the variance is calibrated so that the acceptance probability is reasonable. Chib and Greenberg (1995) provide some rough guidelines on our choices of the variance matrices used in the random walk chains. In particular, the variances for the normal proposal densities are chosen such that for the 3-dimension s_1 vector, the acceptance rate is around .3; for the 6-dimension s_j (j = 2, 3, 4) vectors, the acceptance rate is around .25; and for the univariate s_j (j = 5, 6, 7, 8) the acceptance rate is around .45.

In our empirical application, we take a run of 5,000 replications from our MCMC algorithm and discard the initial 1,000 to mitigate the startup effect. Preliminary runs are used to calibrate the variance matrices for our normal candidate generating densities used in the Metropolis-Hastings algorithm. To compute the marginal likelihood of a model, we follow the method developed by Gelfand and Dey (1994) and modified by Chib and Geweke (1998). Let $p(\theta|M)$ denote the properly normalized prior density in model M, $p(Y|\theta, M)$ denote the properly normalized data density in model M, and let

$$p(Y \mid M) \equiv \int_{\Theta} p(\theta \mid M)\, p(Y \mid \theta, M)\ d\theta \tag{A.20}$$

denote the marginal likelihood of model M. For any p.d.f. $f(\theta)$ whose support is contained in Θ,

$$
\begin{aligned}
E\left[\frac{f(\theta)}{p(\theta|M)\,p(Y|\theta,M)}\,|\,Y,M\right] &= \int_{\Theta}\left[\frac{f(\theta)}{p(\theta|M)\,p(Y|\theta,M)}\right]\frac{p(\theta|M)\,p(Y|\theta,M)}{p(Y|M)}\;d\theta \\
&= \int_{\Theta}\left[\frac{f(\theta)}{p(\theta|M)\,p(Y|\theta,M)}\right]\frac{p(\theta|M)\,p(Y|\theta,M)}{\int_{\Theta} p(\theta|M)\,p(Y|\theta,M)\;d\theta}\;d\theta \\
&= \frac{\int_{\Theta} f(\theta)\;d\theta}{\int_{\Theta} p(\theta|M)\,p(Y|\theta,M)\;d\theta} \\
&\equiv [\,p(Y|M)\,]^{-1}.
\end{aligned}
\tag{A.21}
$$

We approximate (A.21) using simulation output from the MCMC algorithm. More specifically, define

$$\hat{\theta}_N = \frac{1}{N-n}\sum_{i=n+1}^{N}\theta^{(i)},$$

and

$$\hat{\Sigma}_N = \frac{1}{N-n}\sum_{i=n+1}^{N}\left(\theta^{(i)} - \hat{\theta}_N\right)\left(\theta^{(i)} - \hat{\theta}_N\right)',$$

where N is the total number of iterations and there are n burn-in iterations. The dimension of θ is ν. Then for some $p \in (0, 1)$, define

$$\hat{\Theta}_N = \left\{\theta:\left(\theta^{(i)} - \hat{\theta}_N\right)'\hat{\Sigma}_N^{-1}\left(\theta^{(i)} - \hat{\theta}_N\right) \le \chi^2_{1-p}(\nu)\right\},$$

and take

$$f(\theta) = p^{-1}(2\pi)^{-K/2}\,|\hat{\Sigma}_N|^{-1/2}\exp\left[-\tfrac{1}{2}\left(\theta - \hat{\theta}_N\right)'\hat{\Sigma}_N^{-1}\left(\theta - \hat{\theta}_N\right)\right]\mathbf{1}_{\hat{\Theta}_N}(\theta).$$

For a wide range of regular problems, the above function ensures

$$\frac{f(\theta)}{p(\theta|M)\,p(Y|\theta,\,M)}$$

is uniformly bounded and (A.21) is well-defined.

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Table 1: Descriptive Statistics: Mean (Std. Dev. in Mean) [Std. Dev.] of Endogenous Variables and Additional Descriptive Statistics on G and BW

	Variables	White		Black	Hisp.	Native Amer.
		Main	Supp.			
z_1	**S = 1 if mother smoked during pregnancy = 0 otherwise**	.3384	.4674	.2253	.1667	.4198
		(.0156)	(.0309)	(.0210)	(.0213)	(.0552)
		[.4734]	[.4999]	[.4183]	[.3733]	[.4966]
z_2	**D = 1 if mother drank alcohol during pregnancy = 0 otherwise**	.5974	.5747	.3342	.3987	.4198
		(.0162)	(.0307)	(.0238)	(.0280)	(.0552)
		[.4907]	[.4953]	[.4723]	[.4904]	[.4966]
z_3	**PC = 1 if prenatal care started in first trimester = 0 otherwise**	.8466	.8582	.7772	.7418	.8395
		(.0119)	(.0216)	(.0210)	(.0251)	(.0410)
		[.3606]	[.3495]	[.4166]	[.4383]	[.3694]
z_4	**Weight gain net of BW in kg (WG)**	12.08	12.56	11.47	11.86	12.06
		(.1965)	(.4002)	(.3531)	(.3799)	(.8188)
		[5.957]	[6.465]	[7.019]	[6.645]	[7.369]
z_5	**Gestation in weeks (G)**	38.80	38.92	38.71	38.70	39.11
		(.0721)	(.1476)	(.1085)	(.1348)	(.2908)
		[2.185]	[2.384]	[2.157]	[2.358]	[2.617]
	Proportion Preterm (< 37 wks.)	.1251	.1226	.1215	.1046	.0988

	Proportion Very Preterm (< 32 wks.)	.0087	.0153	.0203	.0196	.0247
z_6	**Birth length in cm (BL)**	51.18	50.98	50.15	50.62	51.33
		(.1146)	(.2331)	(.2534)	(.2713)	(.3270)
		[3.473]	[3.766]	[5.037]	[4.745]	[2.943]
z_7	**Birth weight in kg (BW)**	3.367	3.274	3.189	3.224	3.347
		(.0185)	(.0348)	(.0285)	(.0333)	(.0751)
		[.5598]	[.5615]	[.5655]	[.5820]	[.6756]
	Proportion LBW	.0620	.0766	.1063	.1013	.1111
	Proportion VLBW	.0054	.0115	.0076	.0131	.0247
	Minimum BW in kg	1.106	1.191	.5670	.7938	1.276
	Maximum BW in kg	4.905	4.536	4.649	4.763	4.876

Table 2: Descriptive Statistics: Mean (Std. Dev. in Mean) of Exogenous Variables

	Variables	White		Black	Hisp.	Native
		Main	Supp.			Amer.
x_2	**Male child**	.5092	.5326	.4861	.5261	.4815
		(.0165)	(.0309)	(.0252)	(.0286)	(.0559)
x_3	**Mother's age - 23yrs.**	1.381	-.1724	-.7367	-.4542	-.4198
		(.1383)	(.2311)	(.2111)	(.2229)	(.4749)
x_4	**Body mass index (weight in kg / [height in m]^2) - 24**	-.3644	-1.158	.4669	-.1560	.3689
		(.1442)	(.2433)	(.2592)	(.2384)	(.5572)
x_5	**Maternal height - 162cm**	2.323	1.485	1.454	-2.030	.9363
		(.2084)	(.4149)	(.3728)	(.3412)	(.7211)
x_6	**Maternal weight - 63kg**	.8939	-1.861	2.354	-1.951	1.798
		(.4196)	(.7190)	(.7327)	(.6497)	(1.591)
x_7	**Northeast**	.1904	.2069	.1418	.1373	**.0000**
		(.0130)	(.0251)	(.0176)	(.0197)	**(.0000)**
x_8	**South**	.2775	.3640	.5949	.3170	.5926
		(.0148)	(.0298)	(.0247)	(.0266)	(.0549)
x_9	**West**	.1817	.1648	.0759	.4575	.1852
		(.0127)	(.0230)	(.0133)	(.0285)	(.0434)
x_{10}	**Calendar Time - (19)85**	.5190	-1.682	-1.139	-1.003	-1.210
		(.1366)	(.1730)	(.2014)	(.2080)	(.4574)
x_{11}	**(AFQT score / mean of NLSY women of same age) - 1**	.3599	.1210	-.3811	-.2293	.0361
		(.0208)	(.0377)	(.0232)	(.0300)	(.0755)
x_{12}	**Household income in $1000 - 25**	6.522	-4.462	-7.350	-2.897	-3.682
		(.6889)	(.9872)	(.8127)	(1.068)	(1.951)
x_{13}	**No health insurance available**	.5245	.6513	.6785	.6438	.6914
		(.0165)	(.0296)	(.0235)	(.0274)	(.0516)
x_{14}	**Missing health insurance availability**	.3798	.5364	.5797	.4935	.5309
		(.0160)	(.0309)	(.0249)	(.0286)	(.0558)
x_{15}	**Number of adults in household - 2**	.1643	.2375	.6658	.5621	.2716
		(.0233)	(.0430)	(.0608)	(.0718)	(.1069)

x_{16}	**Number of quarters worked during pregnancy - 3**	.1382	-.2720	-.7595	-.3627	-.6296
		(.0450)	(.0981)	(.0848)	(.0922)	(.1614)
x_{17}	**Number of maternal siblings - 4**	-.9097	-.1724	.5544	.6634	-.3086
		(.0628)	(.1476)	(.1505)	(.1656)	(.2610)

Table 2 (continued): Descriptive Statistics: Mean (Std. Dev. in Mean) of Exogenous Variables

x_{18}	**Grandmother's education - 12yrs.**	-.1143	-1.035	-.9975	-4.137	-1.222
		(.0702)	(.1638)	(.1204)	(.2287)	(.2961)
x_{19}	**Not on time in school at age 14**	.0555	.1494	.0937	.1928	.1605
		(.0076)	(.0221)	(.0147)	(.0226)	(.0410)
x_{20}	**Non-urban at age 14**	.2394	.2337	.1823	.1176	.2840
		(.0141)	(.0262)	(.0195)	(.0184)	(.0504)
x_{21}	**No employed male in household at age 14**	.1382	.3257	.4025	.2451	.2469
		(.0114)	(.0291)	(.0247)	(.0246)	(.0482)
x_{22}	**Cigarette price index**	.0851	-.1629	-.0792	-.0821	-.0856
		(.0149)	(.0150)	(.0214)	(.0213)	(.0488)
x_{23}	**Alcohol price index**	.0324	-.0688	-.0469	-.0345	-.0502
		(.0064)	(.0076)	(.0093)	(.0094)	(.0203)
x_{24}	**Medical services price index**	.0674	-.1277	-.0726	-.0664	-.0839
		(.0121)	(.0135)	(.0176)	(.0179)	(.0394)
x_{25}	**Food price index**	.0251	-.0702	-.0468	-.0415	-.0488
		(.0060)	(.0075)	(.0089)	(.0093)	(.0200)

Table 3: Prior Means (Standard Deviations) of Across-Equation Covariances and Variances in Σ Under Both H_* and H_A

	D*	**PC***	**WG**	**G**	**BL**	**BW**
S*	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)
D*		.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)
PC*			.0000 (1.000)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)
WG			66.67 (94.28)	.0000 (1.000)	.0000 (1.000)	.0000 (1.000)
G				8.333 (11.79)	.0000 (1.000)	.0000 (1.000)
BL					8.333 (11.79)	.0000 (1.000)
BW						.3333 (.4714)

Note: Variances for S^*, D^* and PC^* are normalized to unity. Off-diagonal elements are given as covariances.

Table 4: Prior Means (Standard Deviations) of Γ_1 and Γ_2 Under Both H_* and H_A

Endogenous Variable j	$\gamma_{j,G}$	$\gamma_{j,BL}$	$\gamma_{j,BW}$
S	-1.000	.0000	-.3500
	$(2\xi^{1/2})$	$(3\xi^{1/2})$	$(\xi^{1/2})$
D	.0000	.0000	.0000
	$(2\xi^{1/2})$	$(3\xi^{1/2})$	$(\xi^{1/2})$
PC	.0000	.0000	.1000
	$(2\xi^{1/2})$	$(3\xi^{1/2})$	$(\xi^{1/2})$
WG	.0000	.1000	.1000
	$(2\xi^{1/2})$	$(\xi^{1/2})$	$(\xi^{1/2})$
G	**-1.000**	.0500	.0100
	(.0000)	$(\xi^{1/2})$	$(\xi^{1/2})$

Table 5: Prior Means (Standard Deviations) of Δ_1 and Δ_2 Under H_A

	Variables	S	D	PC	WG	G	BL	BW
x_1	**Intercept**	.0000 ($\omega_1^{1/2}$)	.0000 ($\omega_1^{1/2}$)	.0000 ($\omega_1^{1/2}$)	10.00 ($6\omega_1^{1/2}$)	40.00 ($4\omega_1^{1/2}$)	48.00 ($4\omega_1^{1/2}$)	2.000 ($2\omega_1^{1/2}$)
x_2	**Male child**	.0000 ($\omega_1^{1/2}$)	.0000 ($\omega_1^{1/2}$)	.0000 ($\omega_1^{1/2}$)	.0000 ($6\omega_1^{1/2}$)	.0000 ($4\omega_1^{1/2}$)	.1000 ($4\omega_1^{1/2}$)	.1000 ($2\omega_1^{1/2}$)
x_3	**Mother's age - 23yrs.**	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($6\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($2\omega_2^{1/2}$)
x_4	**Body mass index - 24**	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($6\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($2\omega_2^{1/2}$)
x_5	**Maternal height - 162cm**	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($6\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	**.0000** **(.0000)**
x_6	**Maternal weight - 63kg**	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($\omega_2^{1/2}$)	.0000 ($6\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	**.0000** **(.0000)**	.0000 ($2\omega_2^{1/2}$)
x_7	**Northeast**	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($6[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($2[2\omega_1]^{1/2}$)
x_8	**South**	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($6[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($2[2\omega_1]^{1/2}$)
x_9	**West**	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($2\omega_1$)$^{1/2}$	.0000 ($6[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($4[2\omega_1]^{1/2}$)	.0000 ($2[2\omega_1]^{1/2}$)
x_{10}	**Calendar Time - (19)85**	-.2000 ($\omega_2^{1/2}$)	-.2000 ($\omega_2^{1/2}$)	.2000 ($\omega_2^{1/2}$)	.2000 ($6\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($4\omega_2^{1/2}$)	.0000 ($2\omega_2^{1/2}$)
x_{11}	**(AFQT score / mean of same age) -1**	-1.000 ($\omega_1^{1/2}$)	-1.000 ($\omega_1^{1/2}$)	1.000 ($\omega_1^{1/2}$)	1.000 ($6\omega_1^{1/2}$)	.0000 ($4\omega_1^{1/2}$)	.0000 ($4\omega_1^{1/2}$)	.0000 ($2\omega_1^{1/2}$)

x_{12}	**Household income in $1000 - 25**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2^{½})$	.0000 $(4\omega_2^{½})$	.0000 $(4\omega_2^{½})$	.0000 $(2\omega_2^{½})$
x_{13}	**No health insurance available**	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(6\omega_1^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**
x_{14}	**Missing health insurance availability**	.0000 $(2\omega_1)^{½}$	.0000 $(2\omega_1)^{½}$	.0000 $(2\omega_1)^{½}$	.0000 $(6[2\omega_1]^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**
x_{15}	**Number of adults in household - 2**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**
x_{16}	**No. of quarters worked last year - 3**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**
x_{17}	**Number of maternal siblings - 4**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**
x_{18}	**Grandmother's education - 12yrs.**	- .5000 $(\omega_1)^{½}$	- .5000 $(\omega_1)^{½}$	.5000 $(\omega_1)^{½}$	.5000 $(6\omega_1^{½})$	**.0000 (.0000)**	**.0000 (.0000)**	**.0000 (.0000)**

Table 5 (continued): Prior Means (Standard Deviations) of Δ_1 and Δ_2 Under H_A

x_{19}	**Not on time in school at age 14**	.6000 $(\omega_1)^{½}$	.6000 $(\omega_1)^{½}$	-.6000 $(\omega_1)^{½}$	-.6000 $(6\omega_1^{½})$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{20}	**Non-urban at age 14**	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(6\omega_1^{½})$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{21}	**No employed males in household at age 14**	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(\omega_1)^{½}$	.0000 $(6\omega_1^{½})$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{22}	**Cigarette price index**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2)^{½}$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{23}	**Alcohol price index**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2)^{½}$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{24}	**Medical services price index**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2)^{½}$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**
x_{25}	**Food price index**	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(\omega_2)^{½}$	.0000 $(6\omega_2)^{½}$	**.0000** **(.0000)**	**.0000** **(.0000)**	**.0000** **(.0000)**

Table 6: Notational Conventions in Subsequent Tables

	Absolute value of mean between one and two standard deviations
	Absolute value of mean between two and three standard deviations
	Absolute value of mean more than three standard deviations
bold	Standard deviation equal to zero

Table 7: Predictive Means (Standard Deviations) of Reference Mother by Group, Under H_* and H_A: Default Prior

	H_*	H_A	H_*	H_A	H_*	H_A
	Main White		**Black**		**Hispanic**	
S	.4310 (.4952)	.4270 (.4946)	.1710 (.3765)	.1830 (.3867)	.1610 (.3675)	.1720 (.3774)
D	.6070 (.4884)	.5930 (.4913)	.5220 (.4995)	.5070 (.5000)	.5750 (.4943)	.5590 (.4965)
PC	.8370 (.3694)	.8340 (.3721)	.8170 (.3867)	.8200 (.3842)	.7870 (.4094)	.7820 (.4129)
WG	11.50 (6.296)	11.52 (6.279)	10.37 (6.299)	10.43 (6.297)	11.78 (6.301)	11.78 (6.290)
G	38.96 (2.147)	38.83 (2.122)	38.59 (2.148)	38.55 (2.108)	38.74 (2.113)	38.55 (2.111)
BL	50.55 (4.230)	50.49 (4.123)	49.71 (4.205)	49.74 (4.093)	50.54 (4.217)	50.56 (4.115)
BW	3.305 (.5318)	3.279 (.5557)	3.166 (.5337)	3.158 (.5398)	3.258 (.5321)	3.227 (.5364)
	Supplemental White		**Native American**		**Prior**	
S	.4870 (.4998)	.4870 (.4998)	.4310 (.4952)	.4520 (.4977)	.4874 (.4998)	.4958 (.5000)
D	.6430 (.4791)	.6220 (.4849)	.5760 (.4942)	.5540 (.4971)	.4960 (.5000)	.4996 (.5000)
PC	.8730 (.3330)	.8740 (.3318)	.8810 (.3238)	.8720 (.3341)	.4964 (.5000)	.4996 (.5000)

WG	12.13 (6.292)	12.17 (6.287)	11.54 (6.382)	11.51 (6.299)	9.758 (8.926)	9.856 (9.083)
G	38.96 (2.169)	38.81 (2.105)	39.04 (2.192)	38.93 (2.123)	40.11 (26.78)	39.82 (26.90)
BL	50.49 (4.211)	50.48 (4.128)	50.93 (4.245)	50.95 (4.149)	50.49 (50.29)	50.21 (49.72)
BW	3.247 (.5332)	3.220 (.5573)	3.315 (.5325)	3.289 (.5614)	3.161 (50.81)	4.136 (50.34)

Table 8: Posterior Means (Standard Deviations) of Δ_{*j} and Group Dummy Coefficients

Under H_A: Default Prior

x_j	G	BL	BW
Northeast	.1779	.2169	.0207
	(.1788)	(.3114)	(.0422)
South	-.1312	.0458	.0174
	(.1673)	(.2864)	(.0418)
West	.0862	-.1662	.0252
	(.1758)	(.3016)	(.0407)
Cal. Time	-.0837	.0184	.0020
	(.0334)	(.0515)	(.0074)
AFQT	-.0596	-.5700	.0025
	(.1411)	(.2476)	(.0329)
Income	-.0011	-.0077	-.0006
	(.0044)	(.0072)	(.0010)
Supplemental White	.0537	.0738	-.0553
	(.1858)	(.3048)	(.0414)
Black	-.7287	-1.436	-.1910
	(.1948)	(.3187)	(.0451)
Hispanic	-.6406	-.8801	-.1245
	(.2264	(.3517)	(.0514)
Native American	.0380	.6015	.0085
	(.2899)	(.4929)	(.0651)

Table 9: Posterior Means (Standard Deviations) of Across-Equation Correlations and Variances in Σ Under H_*: Default Prior

	D*	**PC***	**WG**	**G**	**BL**	**BW**
S*	.3785 (.0352)	-.0035 (.0440)	.0309 (.0303)	.1555 (.1324)	-.0230 (.1408)	.2356 (.1044)
D*		-.0005 (.0397)	.0525 (.0314)	.3352 (.1295)	-.1052 (.0926)	-.0263 (.1100)
PC*			.0341 (.0301)	-.5304 (.0607)	-.2723 (.0723)	-.4674 (.0665)
WG			40.54 (1.303)	.0422 (.0421)	-.0213 (.0329)	.0382 (.1012)
G				6.255 (.5185)	.3271 (.0498)	.4595 (.0681)
BL					16.24 (.6932)	.4824 (.0308)
BW						.2998 (.0292)

Note: Variances for S^*, D^* and PC^* are normalized to unity. Off-diagonal elements are given as *correlations*, not covariances.

Table 10: Birth Input Equations, Posterior Means (Standard Deviations) Under H_*: Default Prior

	Variables	S	D	PC	WG
x_1	**Intercept**	-.2236 (.0881)	.2798 (.0840)	.9890 (.0905)	11.58 (.4139)
x_2	**Male child**	.0500 (.0605)	.0307 (.0596)	.0672 (.0640)	.2632 (.2753)
x_3	**Mother's age - 23yrs.**	-.0144 (.0158)	.0345 (.0151)	.0641 (.0152)	-.1448 (.0737)
x_4	**Body mass index (weight in kg / [height in m]^2) - 24**	.0360 (.0786)	-.1005 (.0764)	.2033 (.0792)	.2342 (.3814)
x_5	**Maternal height - 162cm**	.0151 (.0232)	-.0227 (.0227)	.0531 (.0236)	.1141 (.1141)
x_6	**Maternal weight - 63kg**	-.0105 (.0291)	.0382 (.0284)	-.0765 (.0293)	-.0224 (.1420)
x_7	**Northeast**	.1033 (.1040)	.0544 (.0976)	.1937 (.1081)	.8277 (.5043)
x_8	**South**	-.1828 (.0822)	-.3933 (.0781)	-.0712 (.0845)	.1602 (.4040)
x_9	**West**	-.0693 (.0905)	-.1188 (.0831)	-.0190 (.0935)	.4939 (.4398)
x_{10}	**Calendar Time - (19)85**	.0330 (.0686)	.0334 (.0638)	.0031 (.0700)	-.4012 (.3427)
x_{11}	**(AFQT score / mean of NLSY women of same age) - 1**	-.3684 (.0623)	.2041 (.0529)	-.0728 (.0598)	-.6616 (.2826)

x_{12}	**Household income in $1000 - 25**	-.0053	.0040	.0073	-.0033
		(.0022)	(.0020)	(.0023)	(.0103)
x_{13}	**No health insurance available**	.0880	-.0826	-.3017	.2348
		(.0931)	(.0889)	(.0921)	(.4531)
x_{14}	**Missing health insurance availability**	-.0614	.0446	.1885	.3009
		(.0952)	(.0935)	(.0943)	(.4773)
x_{15}	**Number of adults in household - 2**	.0136	-.0074	-.0534	-.0545
		(.0320)	(.0303)	(.0315)	(.1626)

Table 10 (continued): Birth Input Equation, Posterior Means (Standard Deviations) Under H_*: Default Prior

x_{16}	**Number of quarters worked during pregnancy - 3**	-.0307	.0249	.0043	.1886
		(.0266)	(.0254)	(.0246)	(.1301)
x_{17}	**Number of maternal siblings - 4**	.0112	-.0125	-.0083	.0071
		(.0132)	(.0119)	(.0133)	(.0626)
x_{18}	**Grandmother's education - 12yrs.**	.0370	.0397	.0033	.1819
		(.0130)	(.0124)	(.0130)	(.0598)
x_{19}	**Not on time in school at age 14**	.2666	-.0014	-.1438	.0971
		(.1033)	(.1018)	(.0994)	(.5108)
x_{20}	**Non-urban at age 14**	-.0933	-.1119	.0527	-.3862
		(.0771)	(.0704)	(.0753)	(.3363)
x_{21}	**No employed male in household at age 14**	-.0047	-.0822	-.0259	.2507
		(.0723)	(.0668)	(.0709)	(.3573)
x_{22}	**Cigarette price index**	-.5953	-.1846	-.6019	2.376
		(.7093)	(.6637)	(.6716)	(3.330)

x_{23}	**Alcohol price index**	-1.481	.0609	.7065	.9987
		(1.582)	(1.398)	(1.487)	(7.670)
x_{24}	**Medical services price index**	.2980	-.4581	-.2460	-.0310
		(1.459)	(1.354)	(1.377)	(6.826)
x_{25}	**Food price index**	1.178	-.2855	-.1842	4.447
		(1.423)	(1.288)	(1.404)	(7.268)
x_{26}	**Supplemental White**	.1604	.1037	.1467	.6343
		(.0959)	(.0937)	(.1090)	(.4649)
x_{27}	**Black**	-.7413	-.2564	-.0384	-1.128
		(.0978)	(.0922)	(.0975)	(.4669)
x_{28}	**Hispanic**	-.7825	-.0866	-.1624	.2781
		(.1086)	(.0971)	(.1124)	(.5068)
x_{29}	**Native American**	.0372	-.0963	.2033	.0366
		(.1485)	(.1451)	(.1742)	(.7542)

Table 11: Birth Output Equations, Posterior Means (Standard Deviations) of Γ_1, Γ_2 and Δ_2

Under H_*: Default Prior

	G	**BL**	**BW**
S	-.2922	-.6132	-.4016
	(.5176)	(.9041)	(.0903)
D	-1.238	.7204	.0591
	(.5218)	(.5879)	(.0935)
PC	2.356	2.186	.5051
	(.3370)	(.5444)	(.0840)
WG	.0098	.0911	.0067
	(.0180)	(.0237)	(.0088)
G	**.0000**	.0319	.0366
	(.0000)	(.0452)	(.0208)
Intercept	37.65	46.30	1.492
	(.4471)	(1.647)	(.7798)
Male child	-.0209	.7886	.0958
	(.1139)	(.1834)	(.0259)
Mother's age - 23yrs.	-.0913	-.0502	-.0168
	(.0171)	(.0294)	(.0044)
Body mass index - 24	-.2109	.0446	-.0295
	(.1343)	(.0221)	(.0068)
Maternal height -	-.0546	.0784	**.0000**
162cm	(.0391)	(.0141)	**(.0000)**

Maternal weight - 63kg	.0953 (.0499)	**.0000** **(.0000)**	.0179 (.0026)
Supplemental White	-.0216 (.1769	-.1850 (.3052)	-.0596 (.0379
Black	-.5038 (.2137)	-.7762 (.3153)	-.2072 (.0431)
Hispanic	-.2460 (.2235)	-.0698 (.3479)	-.1229 (.0468)

Table 11 (continued): Birth Output Equations, Posterior Means (Standard Deviations) of Γ_1, Γ_2 and Δ_2 Under H_* : Default Prior

Native American	-.0592 (.3001)	.3188 (.4639)	-.0118 (.0648)
Height	.0079 (.0093)	.0652 (.0148)	.0087 (.0020)
Weight	.0149 (.0053)	.0170 (.0084)	.0067 (.0013)

Table 12: Predictive Distributions of BW for Mothers of Varying Risk, Under H_*: Default Prior

Group	Very High Risk	High Risk	Reference Mother	Low Risk	Very Low Risk
Main White					
Pr(VLBW)	.0010	.0010	.0000	.0000	.0000
Pr(LBW)	.1330	.1200	.0760	.0710	.0630
Mean (kg)	3.097	3.129	3.305	3.335	3.357
St. Dev. (kg)	.5209	.5280	.5318	.5375	.5320
Supplemental White					
Pr(VLBW)	.0010	.0010	.0000	.0000	.0000
Pr(LBW)	.1560	.1430	.0990	.0900	.0800
Mean (kg)	3.056	3.086	3.247	3.275	3.299
St. Dev. (kg)	.5260	.5267	.5332	.5318	.5343
Black					
Pr(VLBW)	.0010	.0000	.0000	.0000	.0000
Pr(LBW)	.1980	.1850	.1120	.1060	.1030
Mean (kg)	2.978	3.006	3.166	3.187	3.194
St. Dev. (kg)	.5346	.5317	.5337	.5331	.5304
Hispanic					
Pr(VLBW)	.0010	.0010	.0000	.0000	.0000
Pr(LBW)	.1700	.1550	.0820	.0800	.0830
Mean (kg)	3.052	3.089	3.258	3.271	3.276
St. Dev. (kg)	.5356	.5443	.5321	.5297	.5301
Native American					
Pr(VLBW)	.0010	.0010	.0000	.0000	.0000
Pr(LBW)	.1230	.1140	.0760	.0670	.0560
Mean (kg)	3.117	3.146	3.315	3.349	3.376
St. Dev. (kg)	.5220	.5267	.5325	.5321	.5320

Table 13: High/Low Risk Birth Weight Puzzle, Group/Main White Ratios Under H_*: Default Prior

Group/Main White	Very High Risk	High Risk	Reference Mother	Low Risk	Very Low Risk
Supplemental White					
Pr(LBW)	1.173	1.192	1.303	1.268	1.270
Mean	.987	.986	.982	.982	.983
St. Dev.	1.010	.998	1.003	.989	1.004
Black					
Pr(LBW)	1.489	1.542	1.474	1.493	1.635
Mean	.962	.961	.958	.956	.951
St. Dev.	1.026	1.007	1.004	.992	.997
Hispanic					
Pr(LBW)	1.278	1.292	1.079	1.127	1.317
Mean	.985	.987	.986	.981	.976
St. Dev.	1.028	1.031	1.001	.985	.996
Native American					
Pr(LBW)	.925	.950	1.000	.944	.889
Mean	1.006	1.005	1.003	1.004	1.006
St. Dev.	1.002	.998	1.001	.990	1.000

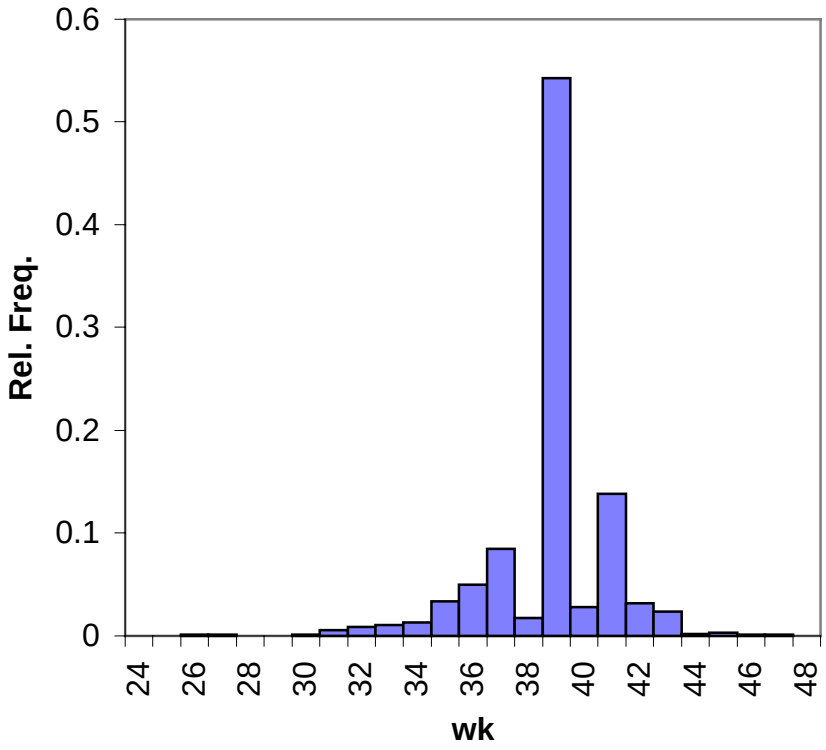
Table 14: Predictive Means of Birth Inputs and G for Mothers of Varying Risk, Under H_* : Default Prior

Group	Very High Risk	High Risk	Reference Mother	Low Risk	Very Low Risk
Main White					
S	.7250	.6480	.4310	.3450	.2780
D	.3640	.4460	.6070	.6920	.7840
PC	.6890	.6860	.8370	.8290	.8230
WG (kg)	12.38	12.23	11.50	11.35	11.21
G (wks)	38.83	38.75	38.96	38.87	38.75
Supplemental White					
S	.7790	.7100	.4870	.4100	.3330
D	.3970	.4970	.6430	.7320	.8150
PC	.7500	.7470	.8730	.8700	.8590
WG (kg)	13.01	12.86	12.13	11.99	11.84
G (wks)	38.90	38.80	38.96	38.86	38.75
Black					
S	.4290	.3540	.1710	.1230	.0860
D	.2840	.3510	.5220	.6070	.6970
PC	.6810	.6740	.8170	.8190	.8080
WG (kg)	11.25	11.10	10.37	10.23	10.08
G (wks)	38.48	38.41	38.59	38.50	38.37
Hispanic					
S	.4220	.3360	.1610	.1170	.0890
D	.3280	.4180	.5750	.6610	.7540
PC	.6270	.6240	.7870	.7820	.7730
WG (kg)	12.66	12.51	11.78	11.63	11.48
G (wks)	38.57	38.50	38.74	38.62	38.48

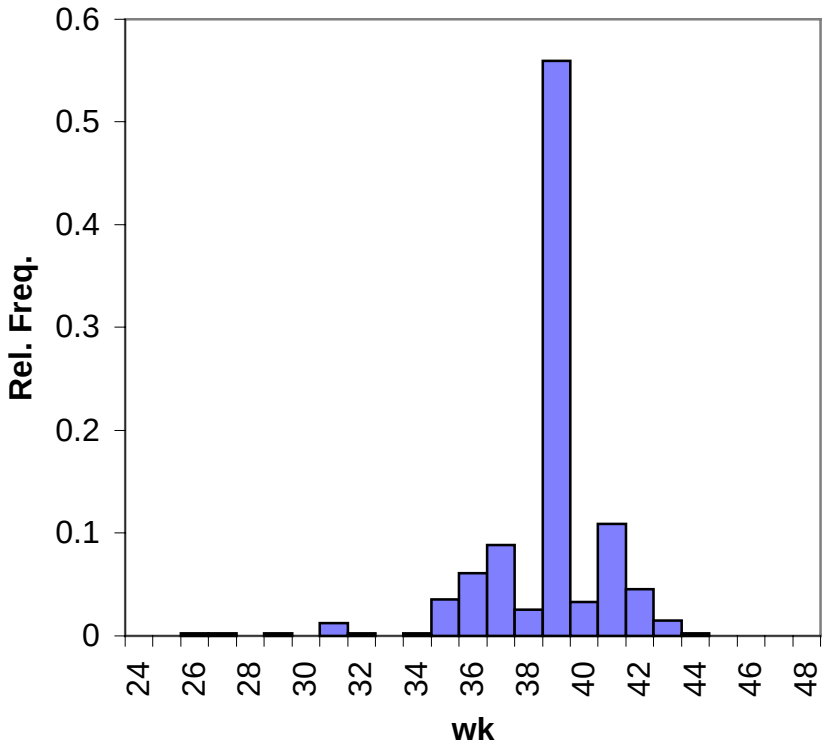
Table 14 (continued): Predictive Means of Birth Inputs and G for Mothers of Varying Risk, Under H_* : Default Prior

Native American					
S	.7420	.6660	.4310	.3490	.2840
D	.3360	.4130	.5760	.6590	.7540
PC	.7580	.7520	.8810	.8780	.8800
WG (kg)	12.41	12.27	11.54	11.39	11.24
G (wks)	38.96	38.88	39.04	38.96	38.86

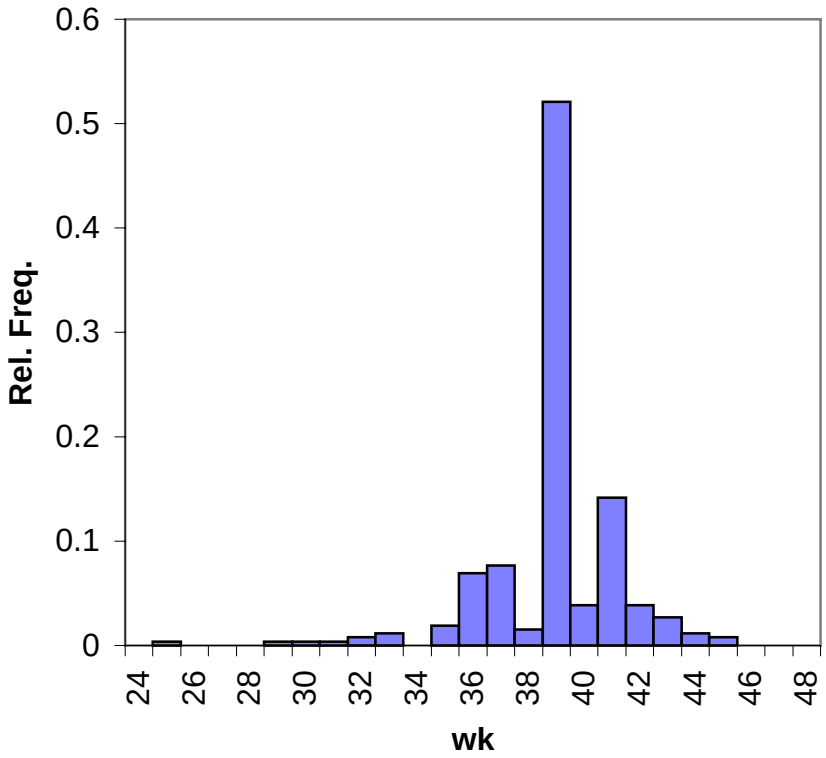
Figure 1: Empirical Histogram for G



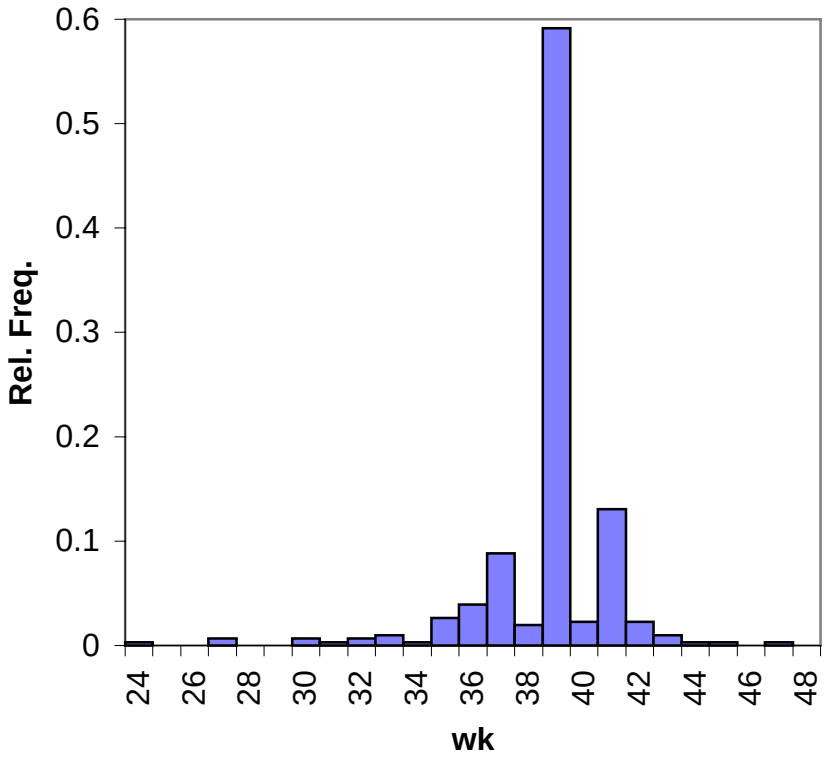
(a) Main White



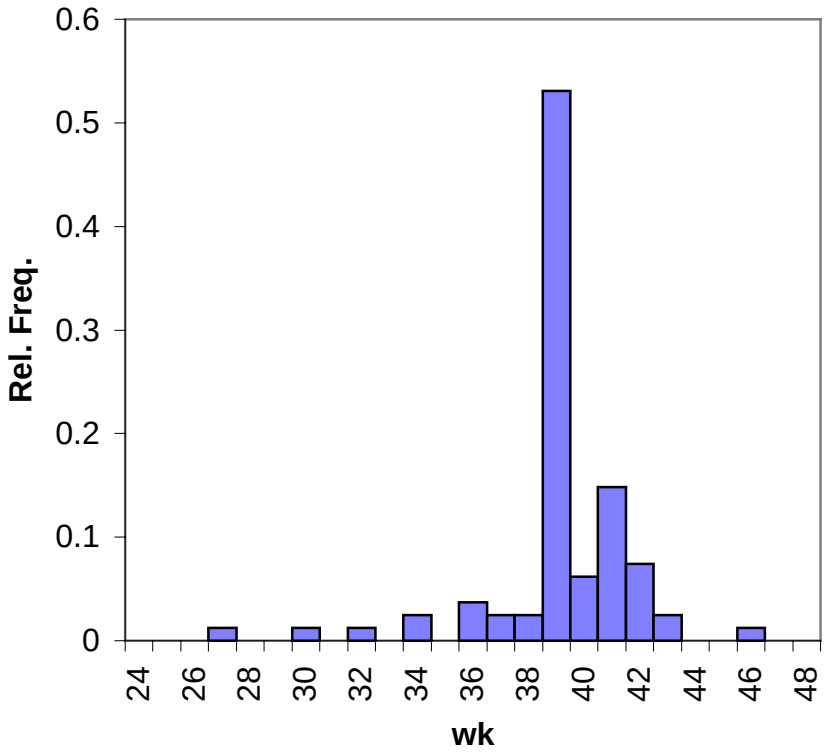
(b) Black



(c) Supplemental White

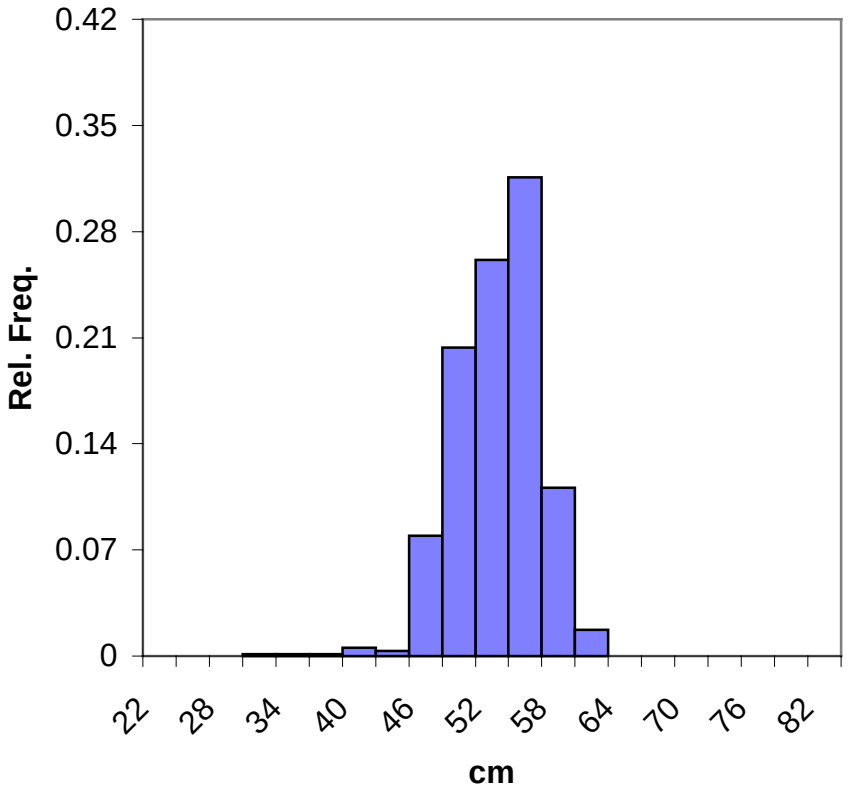


(d) Hispanic

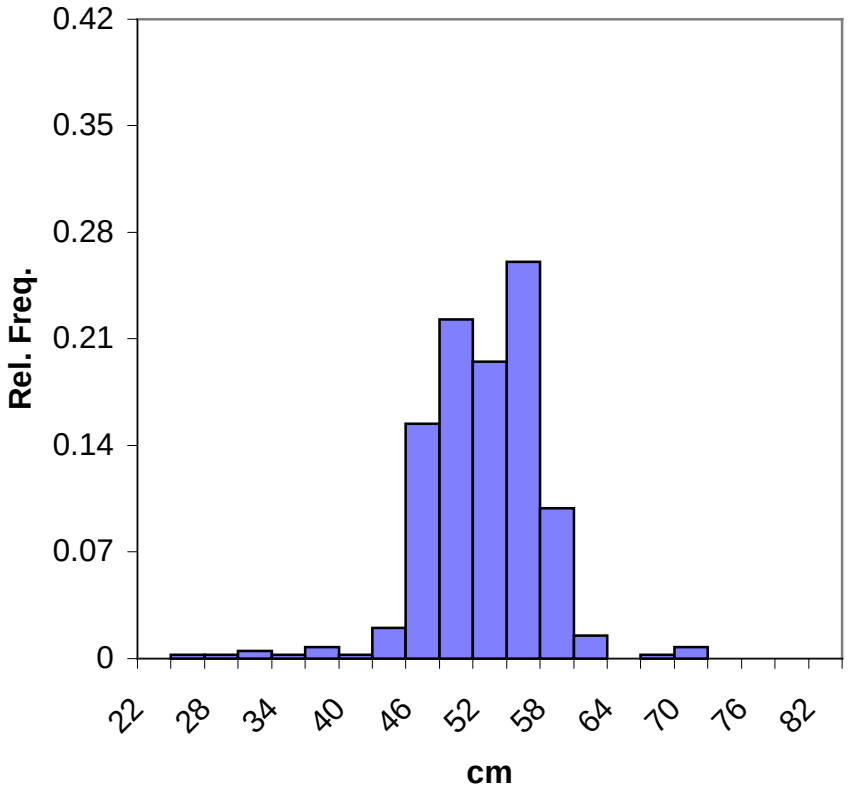


(e) Native American

Figure 2: Empirical Histogram for BL



(a) Main White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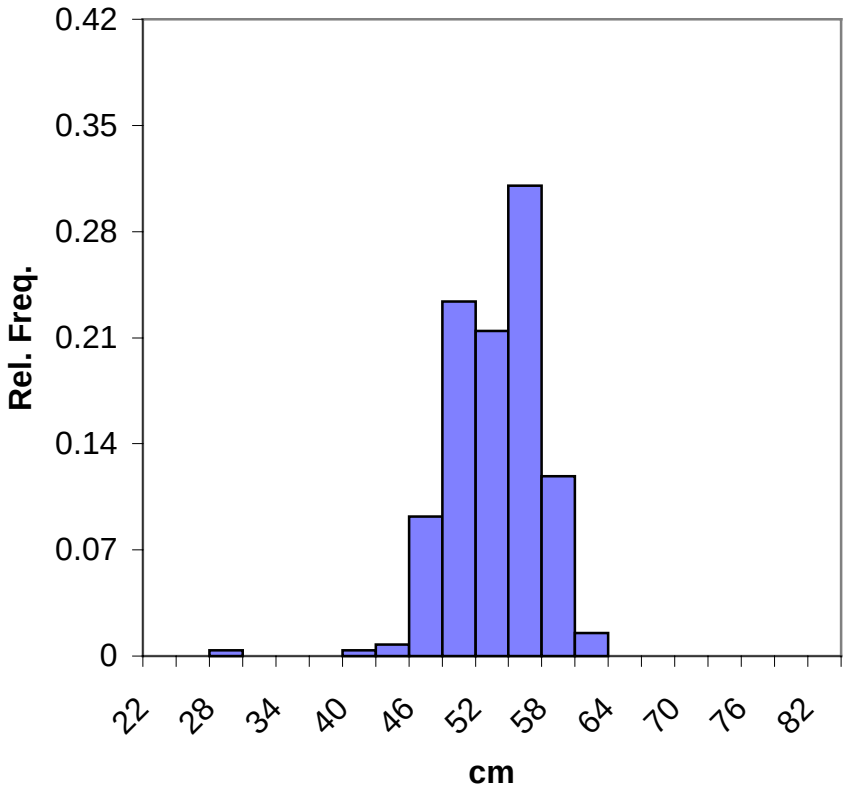
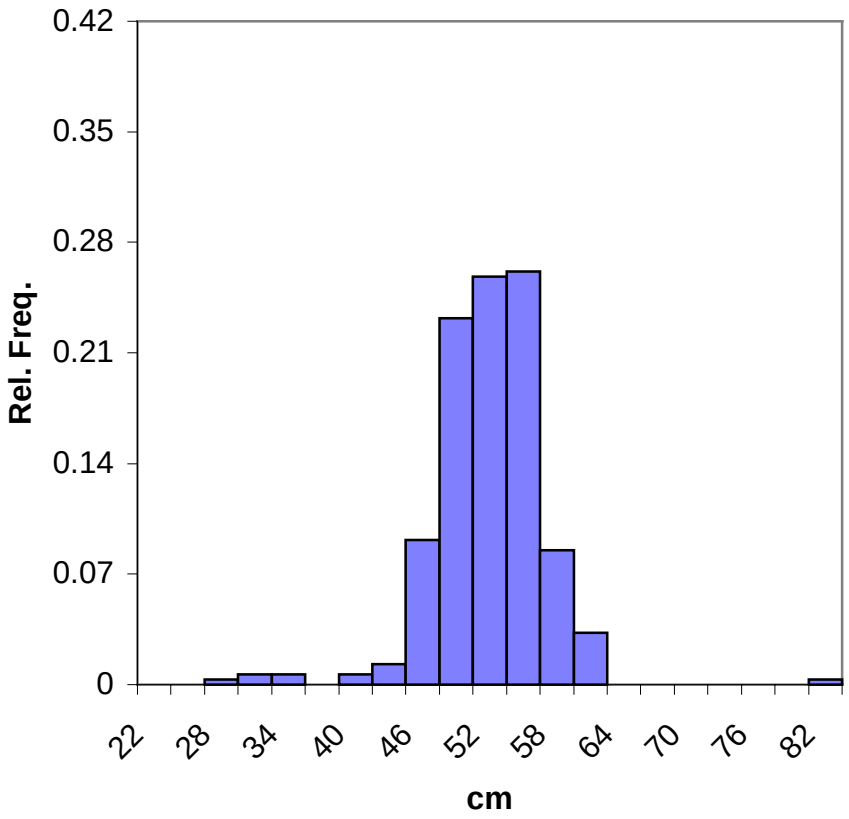
(b) Black



(c) Supplemental White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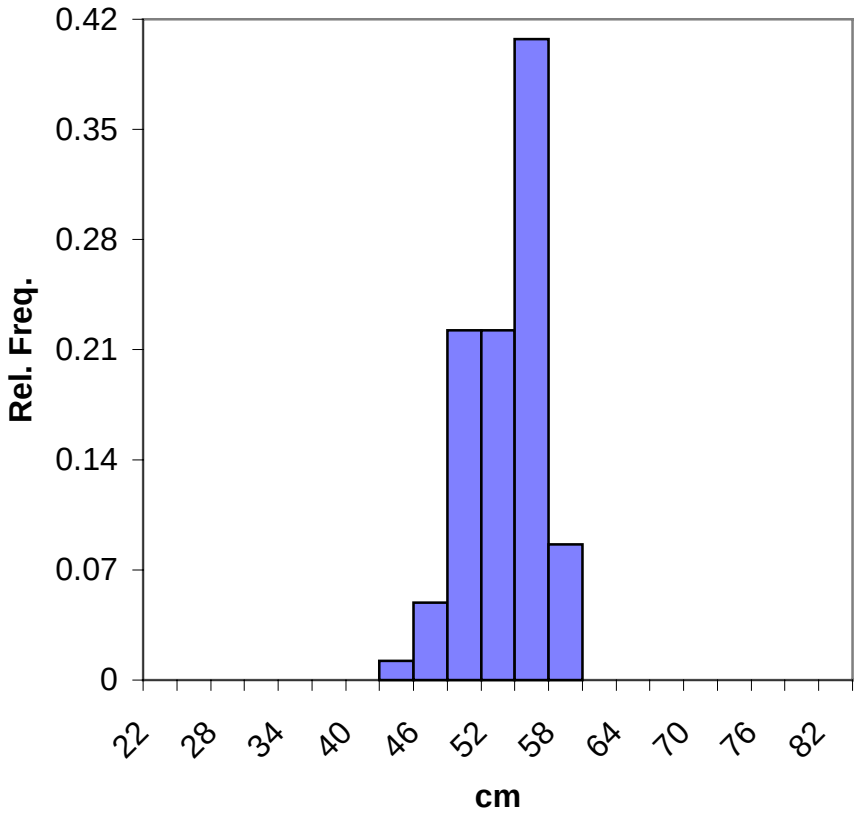
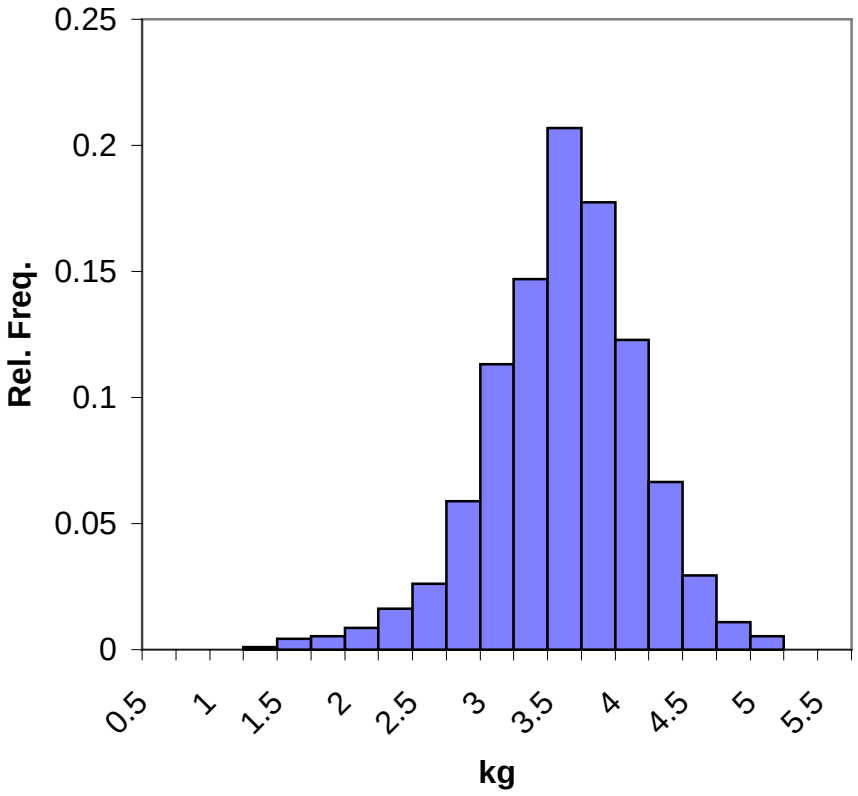
70
76
82
cm

(d) Hispanic

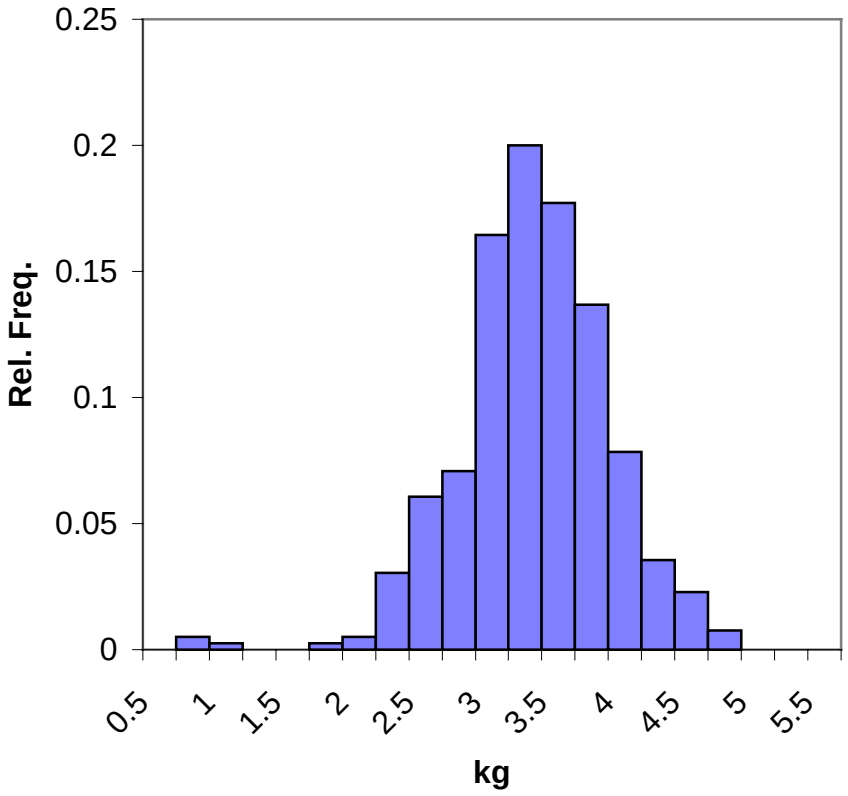


(e) Native American

Figure 3: Empirical Histogram for BW



(a) Main White



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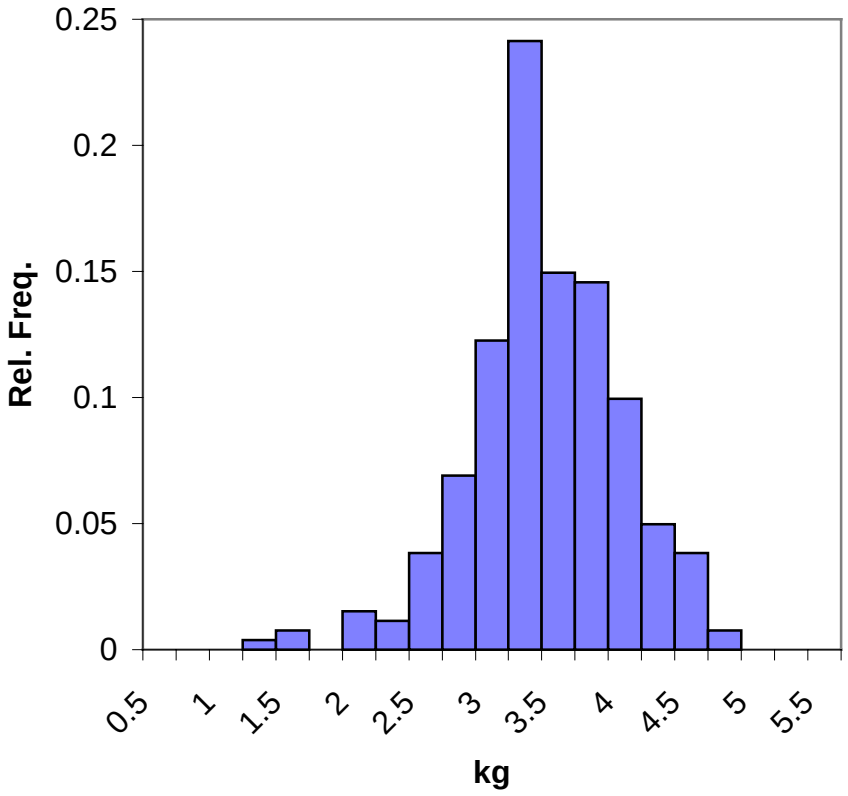
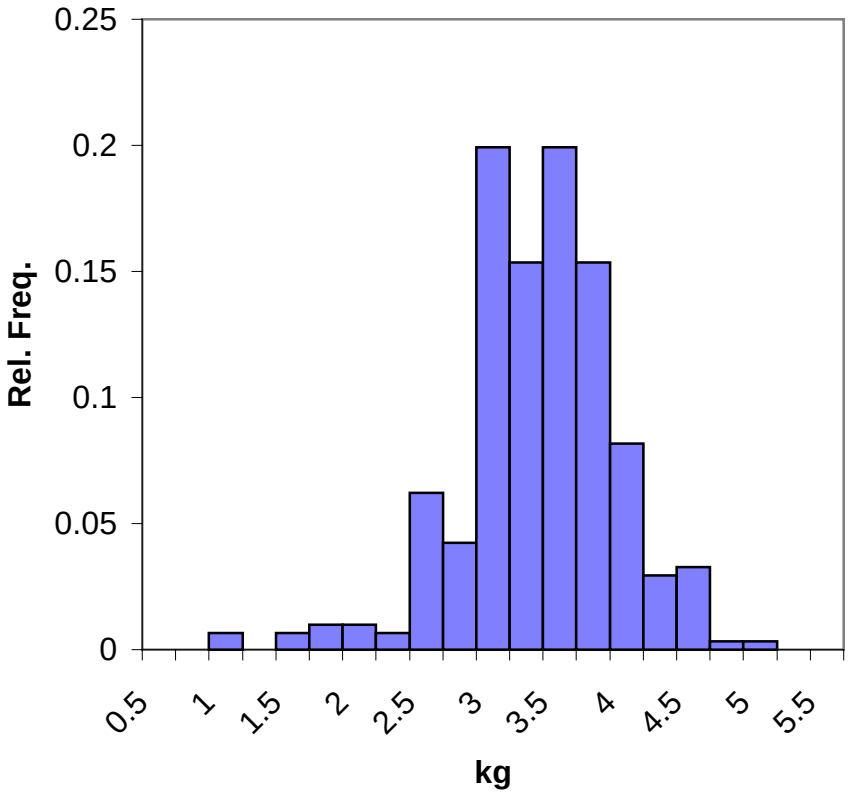
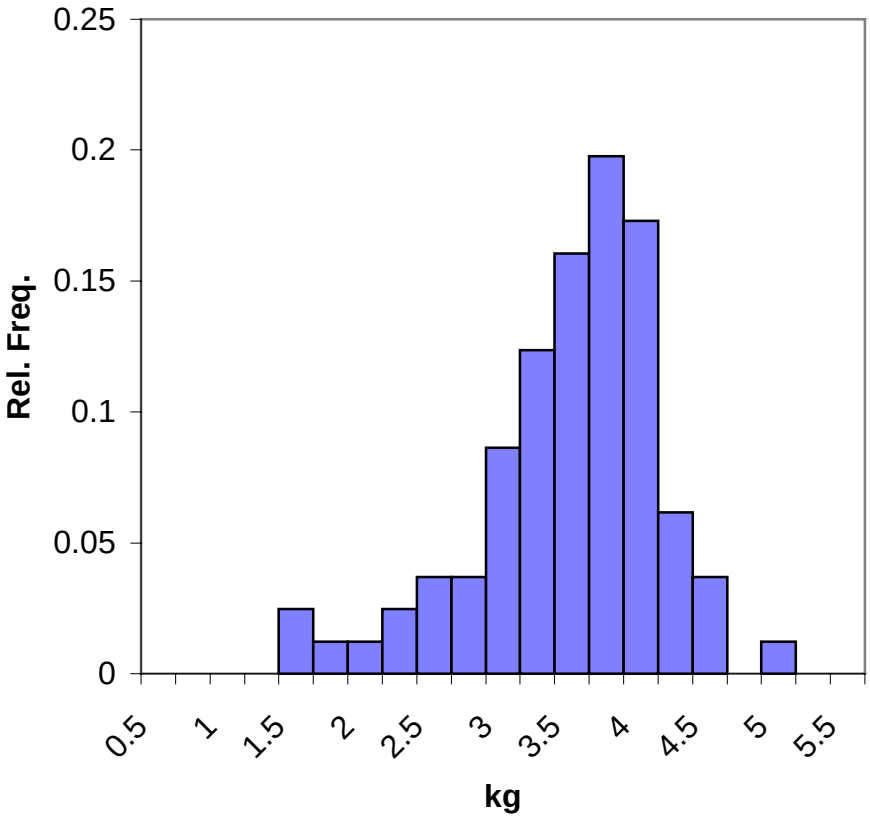


(c) Supplemental White



(d) Hispanic



(e) Native American

Figure 4: Posterior Predictive Distribution for G Under H_*: Default Prior

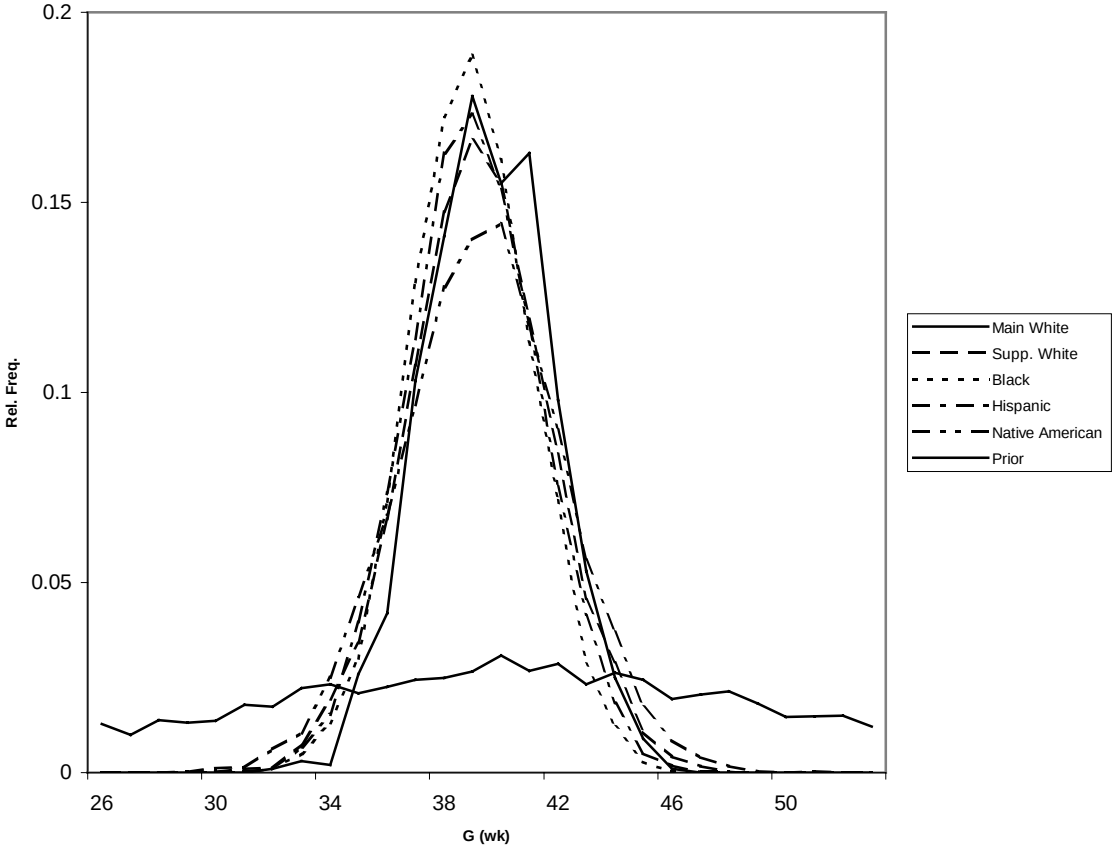


Figure 5: Posterior Predictive Distribution for BL Under H_*: Default Prior

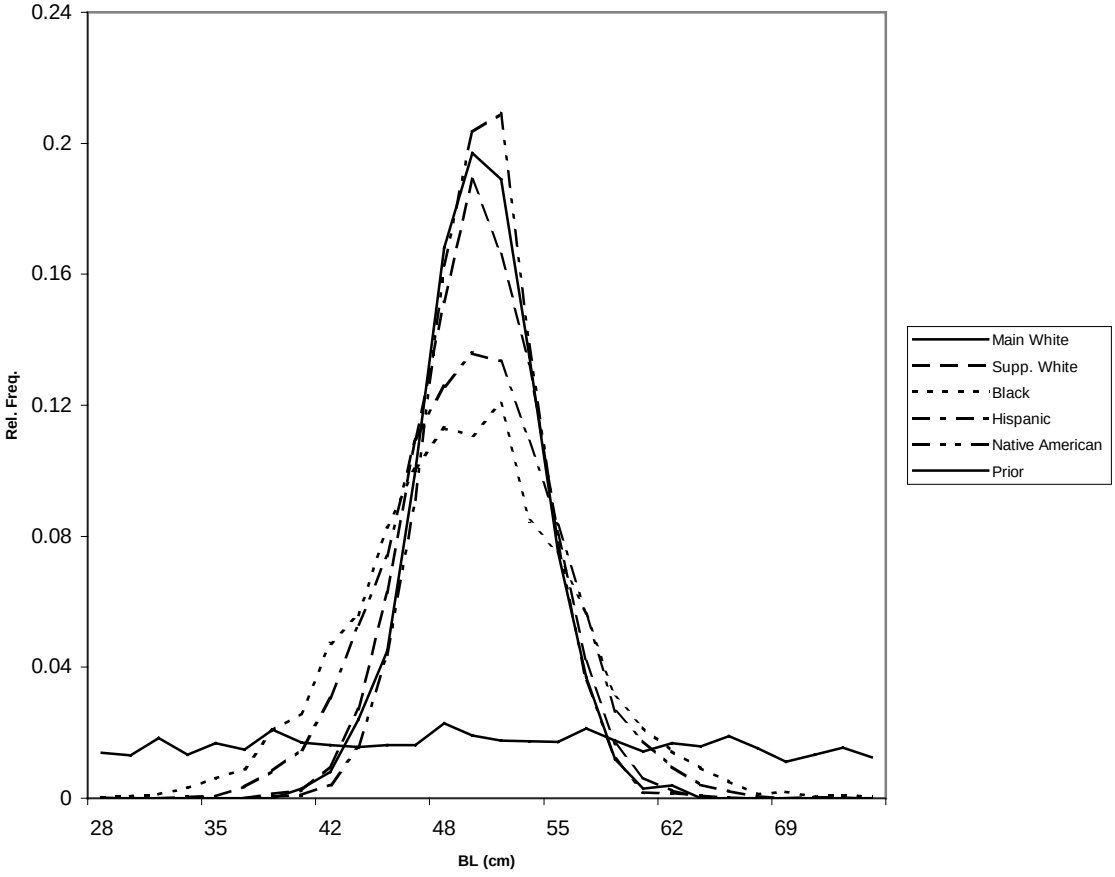


Figure 6: Posterior Predictive Distribution for BW Under H_*: Default Prior

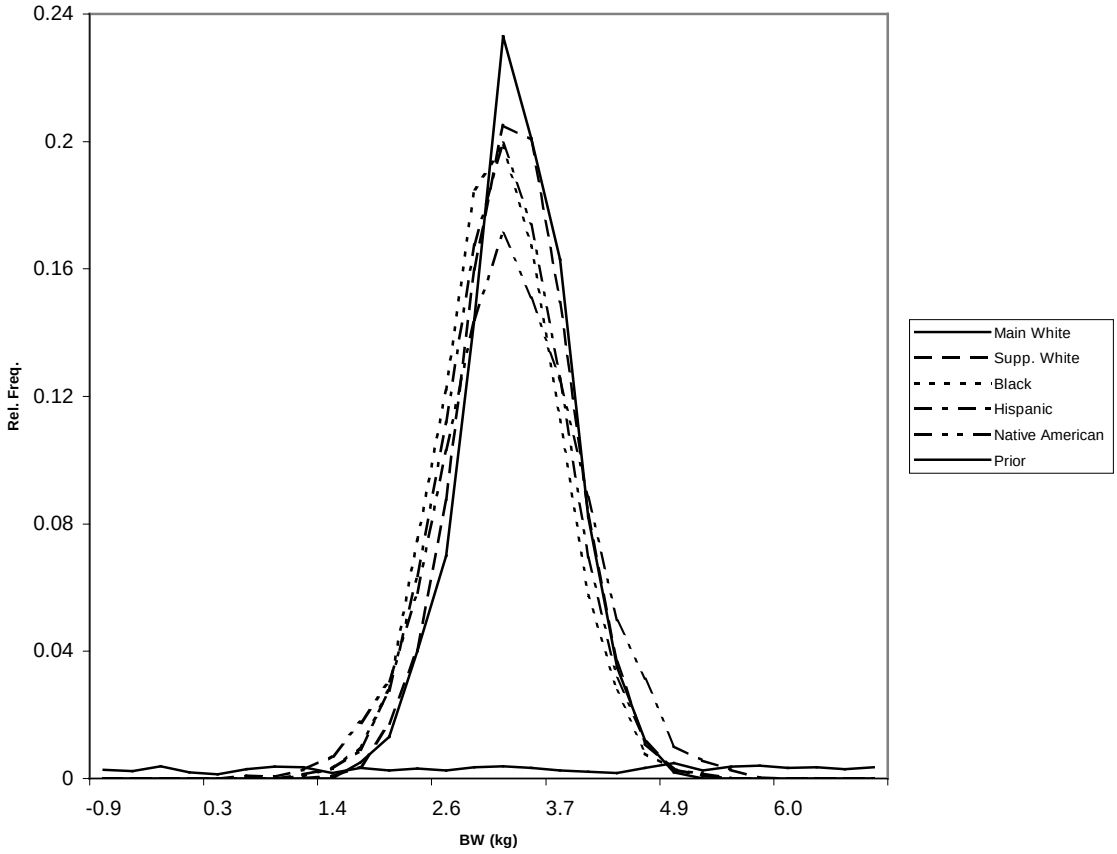
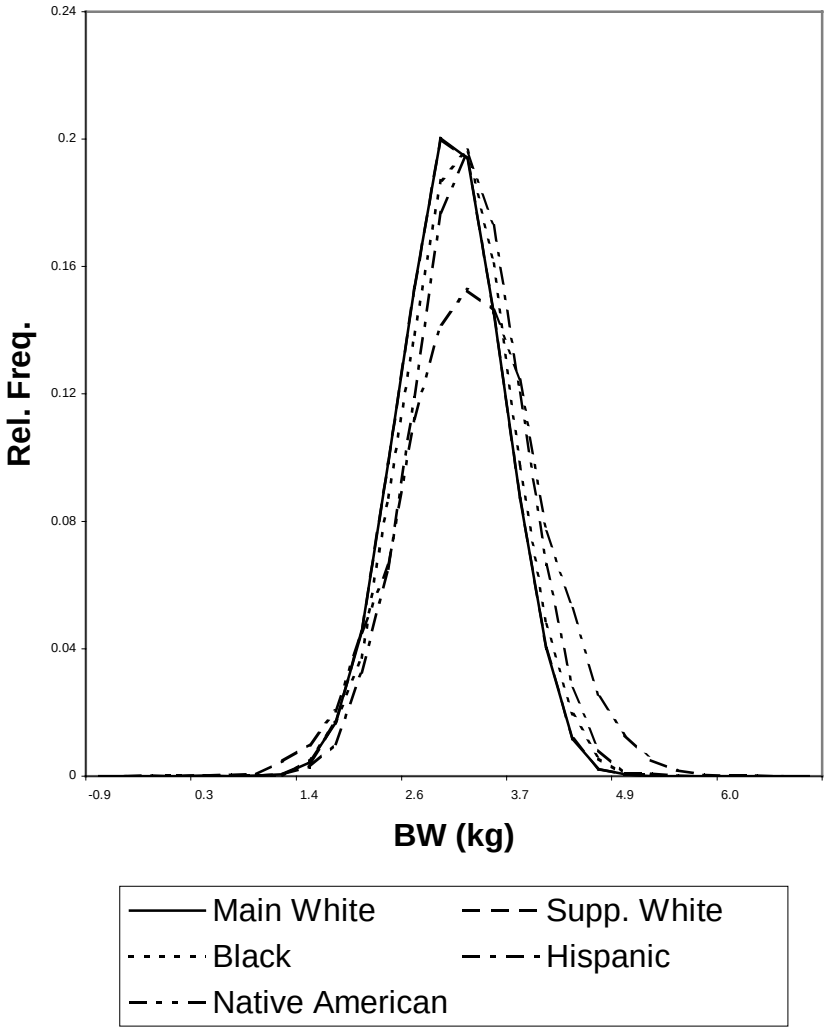
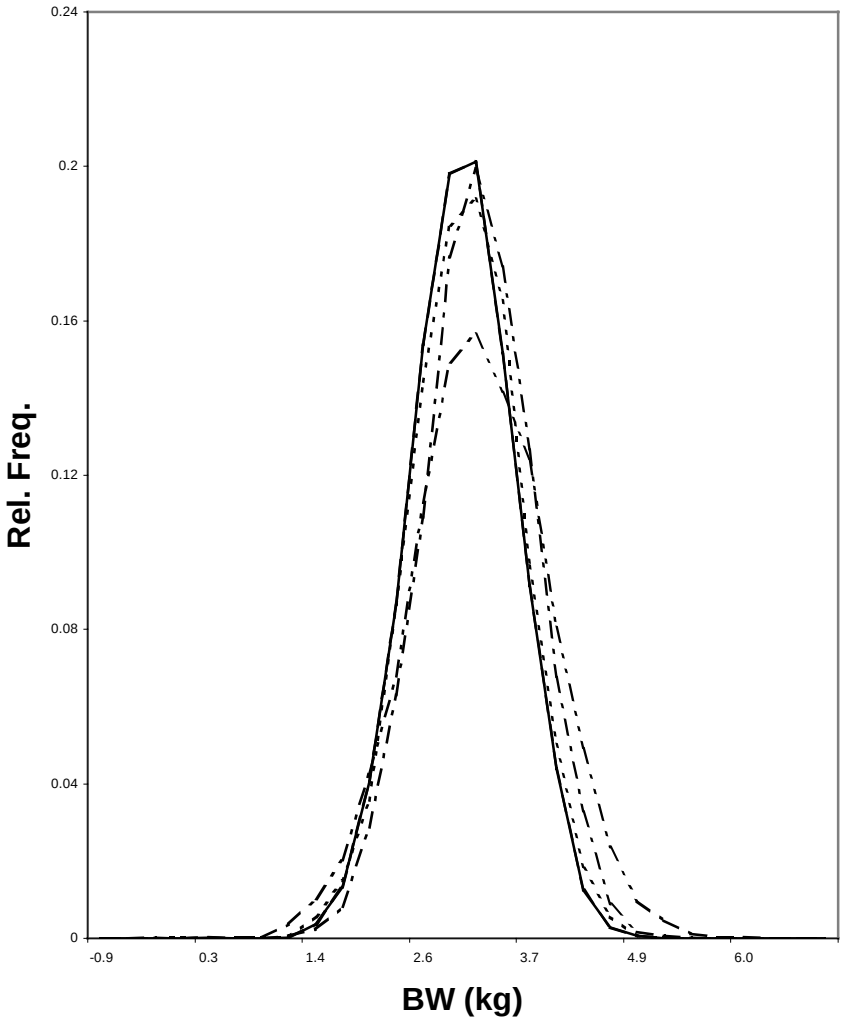


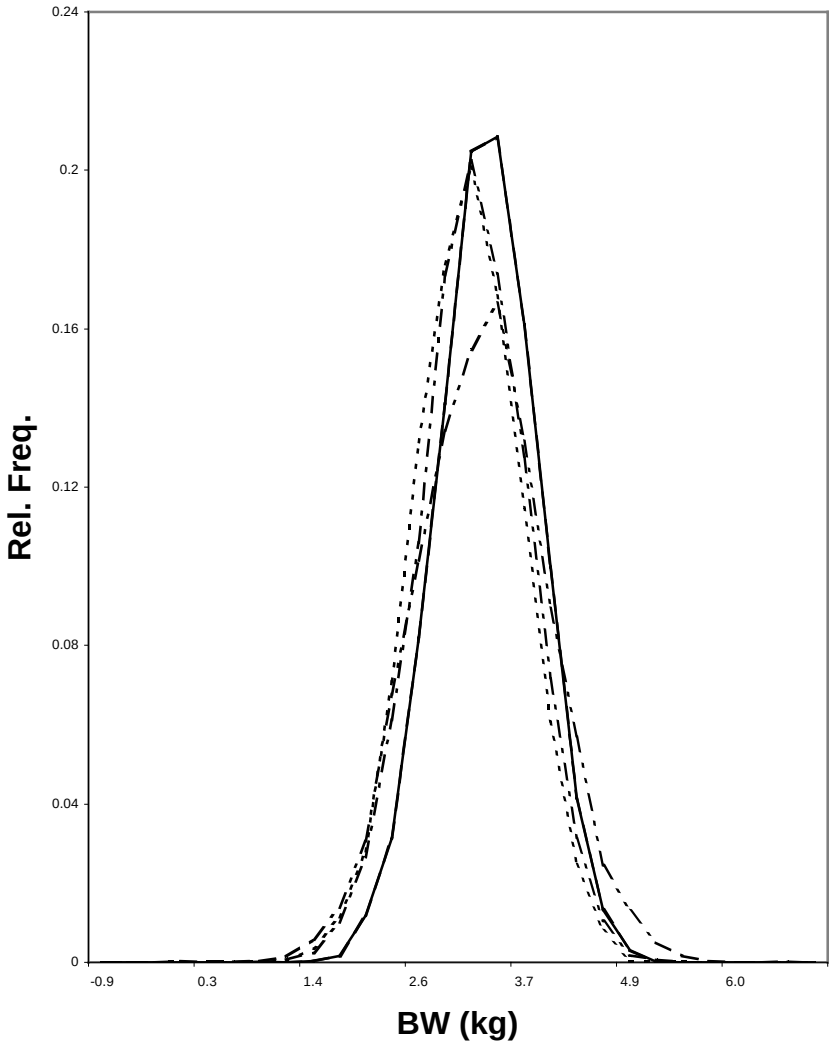
Figure 7: Predictive Distributions of BW for Mothers of Varying Risk, Under H_*: Default Prior



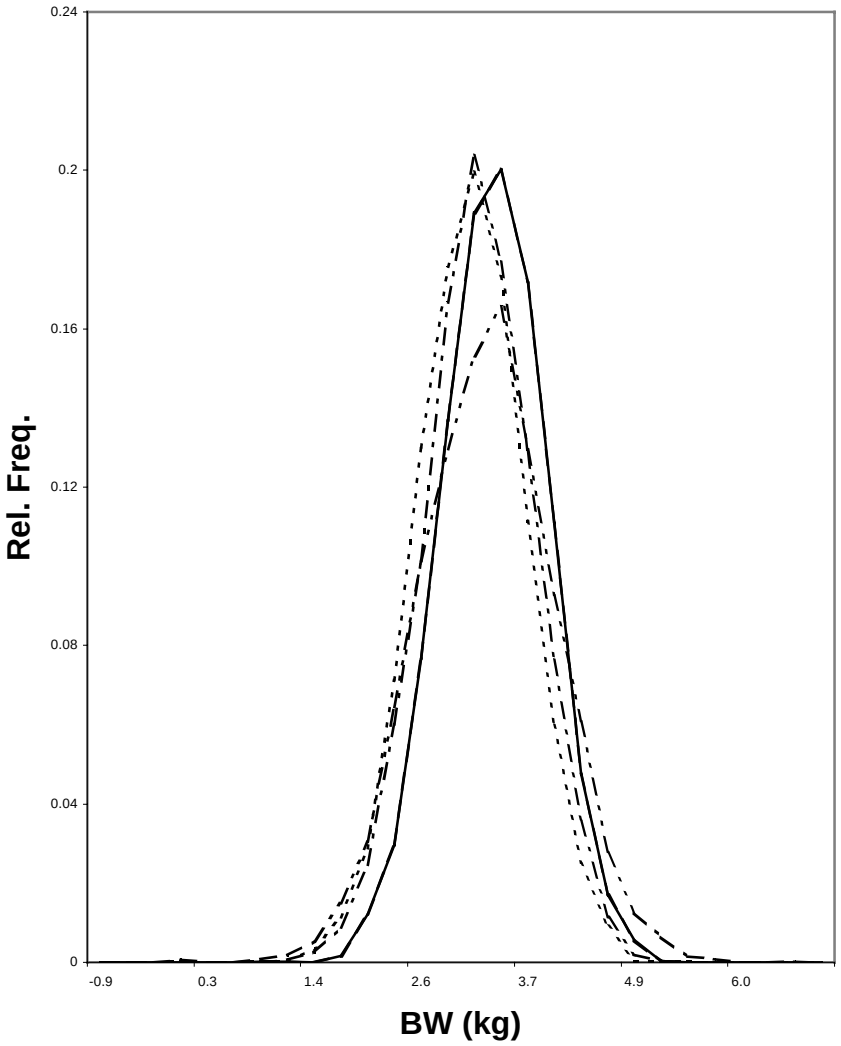
(a) VHR



(b) HR



(c) LR



(d) VLR