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Similarities in Maternal Weight and Birth Weight Across Pregnancies and Across Sisters

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Abstract

Objectives The current study examined how prepregnancy body mass index (BMI), gestational weight gain, and birth weight cluster between births within women and between women who are sisters. *Methods* Using data from the National Longitudinal Survey of Youth 1979 cohort, we utilized nested, multivariable hierarchical linear models to examine the correlation of these three outcomes between births (n = 6006) to women (n = 3605) and sisters (n = 3170) so that we can quantify the clustering by sibship and by woman for these three pregnancy-related outcomes. *Results* After controlling for confounding covariates, prepregnancy BMI (intraclass correlation (ICC) 0.24, 95% CI 0.16, 0.32), gestational weight gain (ICC 0.23, 95% CI 0.16, 0.31), and infant's birthweight (ICC 0.07, 95% CI 0.003, 0.13) were correlated between sisters. Additionally, all three outcomes were significantly correlated between births for each sister, suggesting that prepregnancy BMI (ICC 0.82, 95% CI 0.81, 0.83), gestational weight gain (ICC 0.45, 95% CI 0.42, 0.49), and birth weight (ICC 0.31, 95% CI 0.28, 0.35) track between pregnancies in the same woman. *Conclusions for Practice* The observed clustering both within women and between sisters suggests that shared genetic and environmental factors among sisters play a role in pregnancy outcomes above and beyond that of women's own genetic and environmental factors. Findings suggest that asking a woman about her sisters' pregnancy outcomes could provide insight into the possible outcomes for her current pregnancy. Future research should test if collecting such a family history and providing tailored clinical recommendations accordingly would be useful.

Keywords Birth weight · Body mass index · Gestational weight gain · Pregnancy · Women

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Significance

What Is Already Known on This Subject? Maternal prepregnancy body mass index (BMI) and gestational weight gain (GWG) are associated with infant birth weight, and infants with optimal birth weight have better neonatal and adult health outcomes. Evidence suggests that genetic and environmental risk factors, such as those exposures shared among sisters, may contribute to pregnancy outcomes. *What This Study Adds* Prepregnancy BMI and GWG cluster both between births within women and between sisters, even after controlling for behavioral, social, and childhood factors. This study suggests that shared genetic and childhood environmental factors play a role in pregnancy outcomes.

Introduction

Maternal weight and birth weight have implications for health across the life course and in future generations. Maternal prepregnancy body mass index (BMI) and gestational weight gain (GWG) are associated with infant birth weight (Rasmussen and Yaktine 2009), and infants with optimal birth weight have better neonatal (Wilcox and Russell 1983) and adult health (Risnes et al. 2011) outcomes.

Despite the serious and lasting consequences of unhealthy infant birth weight, identifying prenatal risk factors and increasing access to prenatal care have not reduced the incidence of low birth weight (Lu et al. 2003), and intensive lifestyle intervention in obese mothers does not reduce the risk of high birth weight (Dodd et al. 2014). Many studies have focused on correlations in pregnancy-related outcomes within women, but much fewer have considered correlations within sibships. Siblings share genetic and environmental risk factors for birth weight (McElroy et al. 2012). Intergenerational correlation exists: for example, women who were born low birth weight are more likely to deliver low birth weight infants (Ludwig and Currie 2010). Childhood environment matters: for example, growing up in a low-income household is associated with offspring lower birth weight, even after controlling for current income (Gisselmann 2006). Genetics also has a role: concordance rates and intraclass correlations for birth weight are higher in the offspring of identical twins than fraternal twins (Clausson et al. 2000). Race/ethnicity, which twins also share, is also associated with weight-related outcomes, including GWG (Headen et al. 2012). Both genetic and environmental factors likely contribute to correlated body mass index (BMI) between siblings (Maes et al. 1997). However, we found only two studies, from 1955 (Robson 1955) and 1974 (Johnstone and Inglis 1974), that examined the correlation in the birth weight of infants born to sisters; one study of the GWG correlation between twin sisters (Andersson et al. 2015); and no studies of prepregnancy BMI among sisters. Documenting the extent of the correlation between sisters and within an individual woman will help public health researchers and practitioners understand how much of the determinants of these outcomes are shared within households and within individuals.

The USA's National Longitudinal Survey of Youth 1979 (NLSY79), which sampled siblings, provides a unique opportunity to study within woman and between sister correlations with maternal and infant weight. This analysis investigated whether sisters experience similar pregnancy-related weight and birth outcomes in the NLSY79. We used hierarchical linear models to examine correlations between sisters' prepregnancy BMI, GWG, and infant birth weight, adjusting for pregnancy, maternal, and sibship covariates. We also look at correlations across pregnancies within women.

Methods

The National Longitudinal Survey of Youth 1979 cohort (NLSY79) enrolled a nationwide sample of 12,686 American young men and women who were 14–22 years old when the survey began in 1979; its sampling approach has been described in detail elsewhere (CHRR 2008). The study oversampled Black, Hispanic, and economically disadvantaged White youth. All eligible individuals who resided in a surveyed household were included in the study; as a result, 2862 households had more than one respondent (CHRR 2008). Data were collected on how the respondents were related to every other household member. Multiple respondents per household were most frequently siblings, though some represented spousal pairs and other relationships. Many studies to date using these data have not consider the impact of familial clustering in their analyses, while others use fixed-effects methods to control for the data structure (Bitler and Currie 2005).

Respondents were interviewed in person or on the telephone annually through 1994, and then biennially. Even though these data are not from clinical study or medical data, the original collection of the data was approved by the appropriate ethics committee and all persons gave their informed consent prior to their inclusion in the study. We used follow-up data through 2010, since few women had children thereafter. Since these data are unidentifiable to the specific individual and publicly available, the UC Berkeley

Committee for the Protection of Human Subjects did not require formal review.

The NLSY79 includes 11,377 gestations among 4931 women. Our analytic sample was restricted to singleton births to women at least 15 years of age who had complete data on all variables of interest: 6006 births among 3605 women. The percentage of women with 1, 2, 3, 4, 5, 6, and 7 births was 51.3, 34.2, 11.7, 2.3, 0.5, 0.03, and 0.03%, respectively. The analytic sample included 3,170 sibships, of which 386 (13.9%) sibships had more than one sister who had given birth. These 386 sibships corresponded to 821 women (22.8% of the analytic sample). (Some of these sibships were two sisters, and some sibships included more than two sisters within the same family.)

The outcomes of interest are prepregnancy BMI, GWG, and birth weight. In 1986, participants retrospectively reported information about their pregnancies and births, including infant birth weight. For births after 1986, pregnancy data were collected in the first survey after a pregnancy. Women reporting a pregnancy in the NLSY survey (conducted up to 2 years after the pregnancy) were asked to report their weight just prior to the pregnancy. Prepregnancy BMI [weight (kg)/height (m)^2] was calculated using self-reported prepregnancy weight and the woman's height reported closest to the birth. Gestational weight gain is the difference between prepregnancy weight and a woman's reported weight just prior to delivery. Although these measures were self-reported, a recent systematic review of the literature concluded that women self-report pregnancy-related weight relatively accurately (Headen et al. 2017). We excluded observations with implausible values of gestational age (less than 22 or greater than 44 weeks) (20), and also unlikely combinations of birth weight (grams) and gestational age (weeks), per Alexander et al. (Alexander et al. 1996). Additional pregnancy-related variables were considered as covariates in multivariate models. These variables included infant gestational age, infant gender, prenatal care in the first trimester, cigarette smoking during pregnancy, weekly or more frequent alcohol consumption during pregnancy, and reported calorie reduction during pregnancy.

We also considered baseline characteristics of participants as covariates in multivariate models. Participants in the study were categorized at baseline as Black, Hispanic/Latino, Asian/Pacific Islander, and non-Hispanic White (CHRR 2008). Asian/Pacific Islander women were excluded due to small sample size. Other baseline characteristics included: participant born outside of the United States, and whether they resided in an urban area during childhood. The NLSY1979 study participants reported their own mother's educational attainment, which we categorized into less than high school (< 12 years), high school graduate (12–15 years), or college graduate (≥ 16 years), which we use as a measure of childhood socioeconomic environment (Cohen et al. 2016). We also created a binary family disruption variable defined as if the respondent ever reported any of the following adverse experiences before age 18: in foster care; living in a group home, detention facility, or orphanage; death of a parent; ran away from home; left to live on their own; and/or lived away from parents due to illness, neglect, a court order, or being in trouble. We also included the log-transformed equivalized childhood household income in year 2000 dollars [calculated by dividing the total family income by the size of the family to the 0.38 power (Rehkopf et al. 2010)]. The respondent's education was categorized as less than high school (< 12 years), high school graduate (12–15 years), or college graduate (≥ 16 years) (Cohen et al. 2016).

Hierarchical linear models are the most appropriate statistical approach when observations are naturally clustered (traditional regression models assume observations are randomly sampled). This class of model is used widely for examining when individuals are clustered within schools or neighborhoods (Rabe-Hesketh and Skrondal 2008) and also families (Guo 2005). In contrast to other classes of models, hierarchical linear models allow researchers to quantify the magnitude of clustering within groups, which was the primary objective of this analysis.

Multilevel linear regression techniques (Rabe-Hesketh and Skrondal 2008) were utilized to model the variation in the three outcomes separately with a family structure of 6006 births (level 1) nested within 3605 women (level 2), and 3170 sibships (level 3) (Fig. 1). Multivariate hierarchical linear models are similar to a standard multivariable regression model, but allow researchers to characterize the correlation of exposures and outcomes within clusters and identify what proportion of the variation in the outcomes can be attributed to each level (Rabe-Hesketh and Skrondal 2008). In this study, we estimated the correlation of prepregnancy BMI, GWG, and infant birth weight for births within each woman, and within each sibship due to shared genetic and environmental factors.

The multilevel linear maximum likelihood regressions were run using the xtmixed command in Stata 12.0. Separate three-level multivariate models were used to examine the intraclass correlation coefficients for prepregnancy BMI, GWG, and birth weight. For each outcome, three models were examined. Model 1 was the empty model examining individual and sibship clustering of the outcome with no covariates, Model 2 added maternal (age, equivalized total family income, marital status, educational attainment; for GWG and birthweight models only, also height in meters and prepregnancy BMI) and pregnancy associated covariates (birth year, birth order; for GWG and birthweight models only, also gestational age, early prenatal care, smoked during pregnancy, consumed alcohol during pregnancy, reduced calories during pregnancy, and

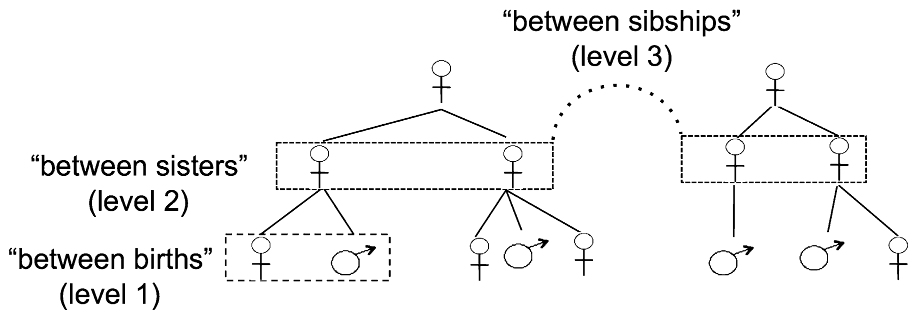

Fig. 1 Example of NLSY three-level data structure. These two family trees show the three levels of our data: births within women within sibships. When we use the phrase "between births," we are comparing outcomes between births to the same woman; when we use the phrase "between sisters," we are comparing outcomes between women who are sisters; when we use the phrase "between sibships," we are comparing outcomes between families

infant gender; additionally, for birthweight model only, GWG was also included), and Model 3, the full model, included all of the variables listed in model 2 plus all sibship covariates (race/ethnicity, foreign born, mother's educational attainment, lived in an urban area as a child, and family disruption). These potential confounders were identified a priori from the literature as characteristics that could be associated within sibships and that were associated with prepregnancy BMI, GWG, and birth weight. Each of these models yielded two intraclass correlations: an estimate of the correlation between pregnancies to the same woman, and an estimate of the correlation between sisters who shared a childhood home. For each model, the residual values for all three levels were evaluated using kernel density plots compared to a normal curve to test the assumption of linearity. For all models and all levels, the residuals were very similar to a normal curve. In addition, with a large sample size, the central limit theorem supports the assumption that the distribution is normal. To test if the models were influenced by outliers, we did sensitivity analyses with only full term births (≥ 37 weeks) and normal birth weight for term (2500–4500 g). All results were comparable.

Intraclass correlations capture the strength of the association between members of the same class: here, births within sibships and births to the same woman. A stronger association implies that taking into account these relationships will yield better predictive ability. To illustrate these findings, we generated sets of predictions from the hierarchical linear model controlling for all covariates (referred to in the results as Model 3), that both take into account these clustering variables and ignore them. Fivefold cross validation was used to obtain honest assessments of predictive performance (Harrell et al. 1996). Mean absolute error (MAE), defined as the average absolute difference between predicted outcomes and observed outcomes, was used as the performance measure for these predictions, because we were interested in the extent to which knowing about sisters' outcomes or previous pregnancies could be useful for predicting a pregnant woman's outcomes for that particular pregnancy.

Results

Descriptive Statistics

The women in the analytic sample were 14.4% Hispanic, 23.5% Black, and 62.1% White (Table 1). A plurality of women had a high school education. The women represented all four regions of the United States, with most living in urban areas. The average age at birth was 26 years, and 70% were married at the time of birth. The mean prepregnancy BMI was within the normal range (BMI of 18–25), and the average GWG was within the recommended range of gain for normal weight women (11.5–16 kg). Eighty-three percent of women received prenatal care in their first trimester and 87.8% of births were full term (≥ 37 weeks gestational age). The average birth weight was 3332 g. Just over 10% of births were small for gestational age or large for gestational age.

When compared to the births not included in the analysis, women in the analytic sample were significantly older than the excluded women by 2.1 years (26.2 years vs. 24.1 years, $p < 0.00005$), more likely to be white (62% vs. 50%, $p < 0.0005$), less likely to smoke during pregnancy (27.9% vs. 31.1%, $p < 0.0005$), and had a slightly higher baseline BMI (23.5 vs. 22.4, $p < 0.00005$). Despite having the same mean gestational age (38.6 weeks), infants in the analytic sample were significantly heavier than the infants not included (3330 g vs. 3250 g, $p < 0.00005$).

Table 1 Population characteristics of the analytic sample

Variable	Analytic sample (n = 3605 women)
Sibship characteristics	
Household size included in NLSY sample, n (%)	
1 woman	2784 (77.2%)
2 sisters	682 (18.9%)
3 sisters	123 (3.4%)
4 sisters	16 (0.4%)
Race, n (%)	
Hispanic	520 (14.4%)
Black	847 (23.5%)
White/Other	2238 (62.1%)
Mother's educational attainment, n (%)	
Less than high school	1675 (46.5%)
High school	1712 (47.5%)
College or more	218 (6.1%)
Born outside of the US, n (%)	229 (6.4%)
Lived in an urban area as a child, n (%)	2846 (79.0%)
Family disruption, n (%)	462 (12.8%)
Variable	**Analytic sample (n = 6006 births)**
Maternal characteristics	
Age at each birth (years), mean ± std dev	26.2 ± 4.9
Equivalized family income (in thousands), year 2000 dollars, mean ± std dev	9.5 ± 1.3
Prepregnancy BMI, mean ± std dev	23.5 ± 4.9
Height (m), mean ± std dev	1.6 ± 0.1
Married, n (%)	4226 (70.4%)
Own educational attainment, n (%)	
Less than high school	1173 (19.5%)
High school	3936 (65.5%)
College or more	897 (14.9%)
Pregnancy characteristics	
Birth year, mean ± std dev	1987 ± 5
Infant gender male, n (%)	3052 (50.8%)
Birth weight (g), mean ± std dev	3332.2 ± 604.7
Smoked during pregnancy, n (%)	1674 (27.9%)
Drank alcohol weekly during pregnancy, n (%)	513 (8.5%)
Reduced calories during pregnancy, n (%)	1523 (25.4%)
Early prenatal care, n (%)	4998 (83.2%)
Gestational weight gain (kg), mean ± std dev	14.2 ± 7.0
Gestational age in weeks, mean ± std dev	38.6 ± 2.1
Full term	5272 (87.8%)

Analytic Statistics

These analyses were based on births nested within women who are sisters (Fig. 1). The intraclass correlation coefficients for between sisters and between births for all models can be found in Table 2. Across the models, for all three levels, the standard deviation decreases with the addition of covariates, indicating that the covariates added to the model explain a portion of the variance in each outcome. The empty model (model 1) estimated the crude intraclass correlations, before adjusting for any covariates for each of the three outcomes. Model 2 included maternal and pregnancy covariates. Model 3 represents the full model, adjusting for all sibship, maternal, and pregnancy covariates.

Between Birth Intraclass Correlations

For prepregnancy BMI, GWG, and birth weight, births to the same woman were significantly correlated (model 1). Adding maternal and pregnancy covariates to the model (model 2) increased the between birth correlation for the maternal outcomes and reduced the between birth correlation for birth weight. In the full model (model 3) with all sibship, maternal, and pregnancy covariates, between birth correlations remained steady and significant (estimates of the associations between the covariates and the outcomes are provided in Table 3 Appendix). In the full model, correlation between births to the same woman explained 82% of the variance in prepregnancy BMI, 45% of the variance in GWG, and 31% of the variance in birth weight.

Between Sisters Intraclass Correlations

Between sister intraclass correlations explained a smaller, yet significant percentage of the variance in all outcomes (model 1). (For example, the between sisters intraclass correlation for birth weight in model 1 was 9%.) The correlations remained significant and relatively steady when maternal and pregnancy covariates were added to the model (model 2) and after adjusting for all sibship, maternal, and pregnancy covariates (model 3). In the full model, between sister intraclass correlation explained 24% of the variance in prepregnancy BMI, 23% of the variance in GWG, and only 7% of the variance in birth weight.

Predictive Performance Analyses

For prepregnancy BMI, the MAE was 3.36 BMI units when only using covariates, which was reduced to 2.73 BMI units when taking into account clustering at the sibship level, and further reduced to 1.80 BMI units when taking into account clustering at the individual level. For gestational weight

Table 2 Intraclass correlation coefficients and 95% confidence intervals

	Model 1	Model 2	Model 3
Prepregnancy BMI			
Between sisters	0.255*** (0.18, 0.33)	0.252*** (0.17, 0.33)	0.242*** (0.16, 0.32)
Between births (within woman and sibship)	0.765*** (0.75, 0.78)	0.821*** (0.81, 0.83)	0.818*** (0.81, 0.83)
Gestational weight gain			
Between sisters	0.222*** (0.15, 0.29)	0.231*** (0.16, 0.30)	0.233*** (0.16, 0.31)
Between births (within woman and sibship)	0.413*** (0.38, 0.45)	0.452*** (0.42, 0.49)	0.452*** (0.42, 0.49)
Birth weight			
Intraclass correlations (95% CI)			
Between sisters	0.092** (0.03, 0.16)	0.073* (0.01, 0.14)	0.065* (0.003, 0.13)
Between births (within woman and sibship)	0.393*** (0.36, 0.43)	0.321*** (0.29, 0.36)	0.312*** (0.28, 0.35)

Model 1: The empty model, with no covariates. Model 2: model 1, plus maternal [age, equivalized total family income, marital status, educational attainment, height in meters, and prepregnancy BMI (as appropriate)] and pregnancy-related (birth year, birth order, gestational age, early prenatal care, smoked during pregnancy, consumed alcohol during pregnancy, reduced calories during pregnancy, infant gender, and gestational weight gain (as appropriate) covariates added. Model 3: The full model: model 2, plus sibship-related covariates (race/ethnicity, foreign born, mother's educational attainment, lived in urban area as child, family disruption) added

***$p < 0.0005$, **$p < 0.005$, *$p < 0.05$

gain, the MAE was 5.06 kg when only using covariates, 4.57 kg when taking into account clustering at the sibship level, and 4.28 kg when taking into account clustering at the individual level. For birthweight, the MAE was 367 g when only using covariates, 357 g when taking into account clustering at the sibship level, and 339 g when taking into account clustering at the individual level.

Discussion

In this national sample, after adjusting for shared and current factors from across the life course, prepregnancy BMI, GWG, and birth weight were significantly correlated between sisters and across multiple births to the same woman. These results suggest that shared genetic and social/environmental factors (as reflected by sibships) likely contribute to prepregnancy BMI and GWG but only a weak correlation exists between sisters for the birth weights of their children. The MAE results further demonstrate that knowing about a woman's prior pregnancies and her sister's prior pregnancies, in addition to individual-level covariates, can be useful in predicting outcomes for her current pregnancy.

This study adds to the literature more generally about shared family characteristics and weight. Genetics may explain 20–80% of the variation in BMI (Maes et al. 1997; Risnes et al. 2011), and family background characteristics, along with genetic factors, are involved in the correlation in BMI among adult siblings (Brown and Roberts 2012; McElroy et al. 2012). While we found some studies that assessed GWG in consecutive pregnancies (Chin et al. 2010; Waring et al. 2013), the most informative study, of correlations in GWG among twin women in Sweden (Andersson et al. 2015), found that shared childhood environmental factors (e.g., family background and shared behaviors) explained more of the variation in GWG than genetic factors, especially for second pregnancies. The literature on the role of specific genes and alleles in GWG is limited (Ludwig and Currie 2010; Rasmussen and Yaktine 2009), and has had inconsistent findings (Lawlor et al. 2011). However, genetic determinants of maternal obesity exist (Li et al. 2016). Additionally, maternal genotype is associated with child birth weight (Tyrrell et al. 2016), and estimated to account for 20–40% of the variance in child birth weight (Gisselmann 2006). While evidence of maternal childhood environmental factors impacting birth weight exists (e.g., Astone et al. 2007; Gavin et al. 2012; Harville et al. 2010), we found no research on the role of shared childhood environmental factors in sisters' pregnancy-related weight outcomes. We found only two studies on the correlation of birth weight between sisters' births, which were published over 40–60 years ago (Johnstone and Inglis 1974;

Robson 1955). The one that calculated a correlation (Robson 1955) estimated a correlation of 13.5%, which is higher than our crude correlation of 9%; future research should help understand if and how these correlations may differ by birth cohort. Further, the adjusted correlation of birthweight between sisters in this sample was only 7% compared to the adjusted between-sisters correlations of prepregnancy BMI and gestational weight gain of 24 and 23%, respectively. This discrepancy suggests that important factors influential of variations in infant birthweight not assessed in the current study do not influence, or less severely influence, variations in maternal prepregnancy BMI and gestational weight gain. Examples of such factors include fetal genes inherited from the father (Magnus et al. 2001), and maternal prenatal stress (Bussières et al. 2015).

The significant correlations in prepregnancy BMI, GWG, and birth weight suggest pregnancies in the same woman are similar. Given the role of weight-related set points (Speakman et al. 2011), a high correlation in prepregnancy BMI within the same woman is expected. The correlation between GWGs for the same woman over her life course, however, is new and interesting, given how many other factors vary between pregnancies, and given that this correlation remains after controlling for other observable factors. This finding suggests that collecting a personal history of GWGs in previous pregnancies would be clinically relevant and could inform clinicians' recommendations and clinical care plan for the current pregnancy. Our unadjusted within-respondent correlation for birth weight in our study falls within this range of 0.40–0.50 identified by other studies (e.g., Beaty et al. 1997, 1988), but decreases to 0.32 after adjusting for pregnancy, maternal, and sibship covariates. This finding suggests that predictions that account for clustering at the sibship and individual woman levels may be more accurate than those predictions that do not.

Our study had some limitations. We used self-reported height and weight, which can be biased, but is often relatively accurate around the time of pregnancy (Headen et al. 2017). We did not have information about health behaviors relevant to weight (e.g., diet, physical activity), so we could not adjust for those characteristics, although those health behaviors would likely mediate any woman- or sibship-specific effects. Also, due to some differences between those who were included and those who were excluded from our analytic sample, inferences should be limited to similar populations (e.g., women whose infants are typical weight for gestational age). We also note that due to our focus on clustering, we were unable to also use the NLSY sampling weights to make this population nationally representative.

Our study also had important strengths. The NLSY data structure allowed us to estimate a three-level model of multiple pregnancies within women who are sisters. The NLSY has more information on social factors across the life course than most studies of pregnancy-related weight, allowing us to be one of few studies to adjust for childhood social factors shared by sisters and current social factors in our models.

Our epidemiological study suggests the life course and the family play an important role in maternal and child health outcomes. For clinicians, asking a woman about her history of weight gain in prior pregnancies (or, for her first pregnancy, her sisters' histories of pregnancy-related weight) could provide insight into possible increased risk of low or excessive weight gain for her current pregnancy, when there is a possibility of intervening. While a woman might not know her sister's exact pre-pregnancy BMI or GWG, she might know if her sister's gain was excessive or inadequate, and/or follow-up with her sister to ask. As weight and height are typically measured at every clinical interaction, clinicians could likely relatively easily review a woman's prior history of weight gain during pregnancies and also for her sister to access her own medical records. Future research should test if collecting such a history and providing tailored clinical recommendations accordingly would be useful. This recommendation is comparable to recommendations others have made to collect family history of more common diseases for which causes are not yet fully understand but for which trends nevertheless occur among family members (Guttmacher et al. 2004). For life course epidemiologists, this study provides new data supporting the importance of early life shared social factors and/or heredity on outcomes in adulthood and potentially into the next generation. In the longer-term, we encourage future researchers to use prediction models to better understand the etiology of life course determinants of pregnancy-related weight and birth weight outcomes.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 3.

Table 3 Multivariate model covariate coefficients and 95% confidence intervals

Variable	Prepregnancy BMI	Gestational weight gain (kg)	Offspring birth weight (g)
Sibship characteristics			
Black	1.44*** (1.03, 1.84)	−0.04 (−0.60, 0.52)	−150.38*** (−188.34, −112.42)
Hispanic	0.68** (0.15, 1.19)	−0.23 (−0.94, 0.48)	9.67 (−37.99, 57.34)
Foreign born	0.07 (−0.61, 0.76)	−0.53 (−1.43, 0.37)	41.06 (−19.84, 101.96)
Mother's education in household: less than high school (reference group: high school degree)	0.60*** (0.24, 0.96)	0.38 (−0.09, 0.86)	−40.16* (−72.57, −7.75)
Mother's education in household: college or more (reference group: high school degree)	−0.15 (−0.85, 0.54)	0.09 (−0.85, 1.01)	−17.19 (−79.72, 45.34)
Lived in an urban area as a child	−0.44* (−0.82, −0.05)	0.17 (−0.34, 0.68)	−12.54 (−47.07, 21.99)
Family disruption	−0.14 (−0.60, 0.33)	0.79* (0.17, 1.40)	−11.04 (−53.05, 30.97)
Maternal characteristics			
Age, mean ± std dev	0.11** (0.04, 0.18)	−0.07 (−0.17, 0.03)	2.84 (−3.97, 9.65)
Equivalized total family income in year 2000 thousands of dollars	0.06 (−0.03, 0.15)	−0.02 (−0.19, 0.16)	−5.51 (−18.51, 7.49)
Married	0.49*** (0.25, 0.73)	−0.09 (−0.55, 0.37)	76.74*** (43.14, 110.34)
Education: less than high school (reference group: high school degree)	0.24 (−0.11, 0.60)	−0.24 (−0.80, 0.32)	−29.34 (−68.70, 10.03)
Education: college or more (reference group: high school degree)	−0.97*** (−1.41, −0.53)	−1.04** (−1.69, −0.39)	24.20 (−21.04, 69.44)
Prepregnancy BMI		−0.39*** (−0.43, −0.35)	16.75*** (13.83, 19.67)
Height in meters		8.82*** (5.33, 12.31)	1255.52*** (1013.49, 1497.55)
Pregnancy characteristics			
Birth year	0.18*** (0.11, 0.24)	0.21*** (0.13, 0.30)	−4.62 (−10.89, 1.64)
Birth order	0.01 (−0.09, 0.12)	−0.64*** (−0.82, −0.46)	47.60*** (34.31, 60.99)
Gestational age in weeks		0.38*** (0.30, 0.45)	128.98*** (123.25, 134.72)
Early prenatal care		0.04 (−0.39, 0.47)	23.17 (−9.06, 55.44)
Smoked during pregnancy		−0.43 (−0.87, 0.01)	−190.30*** (−221.86, −158.75)
Alcohol consumption during pregnancy		−0.34 (−0.93, 0.25)	−12.02 (−55.93, 31.88)
Reduced calories during pregnancy		−0.68*** (−1.07, −0.30)	−8.57 (−37.21, 20.08)
Infant gender male			132.65*** (109.30, 155.99)
Gestational weight gain			13.10*** (11.26, 14.95)

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

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