Introduction

Weight gain in pregnancy has been associated with both maternal and child health outcomes (National Research Council and Institute of Medicine (IOM), 2007), and as a modifiable risk factor is an important focus of research. Women of reproductive age are entering pregnancy heavier than ever before, and a more rigorous methodology for examining the impact of weight gain on several maternal and infant health outcomes is warranted.

Our goal was to develop new statistical methodology to make flexible inferences on the relationship between the functional predictor, longitudinally-measured pregnancy weights, and health outcomes. This goal applies directly to the MCHB strategic issues IV (promoting the health and development of MCH populations) and II (elimination of health disparities). The primary contribution of the statistical component is to limit parametric distributional assumptions inherent in many existing latent trajectory modeling and joint modeling approaches. In order to make the most appropriate recommendations to women and influence prenatal care practices, these new statistical methods are needed to better characterize the association between the pattern and amount of pregnancy weight gain and health outcomes.

In order to achieve our goals, we analyzed data from three sources: the UNC Pregnancy, Infection, and Nutrition (PIN) study, the 1988 National Maternal and Infant Health Study (NMIHS), and the Norwegian Mother and Child Cohort Study (MOBA).

In the PIN data, we studied the relationship between the pattern of weight gain and birth outcomes, finding evidence of different weight gain trajectories by pregravid BMI. Moderate sample sizes led to the need for new statistical methods for partial stratification in trajectory models, which are currently being finalized. We have submitted two statistical methods manuscripts with plans for at least one more, and we have submitted four manuscripts in subject matter literature, with plans for another once the partial stratification methods are finalized.

In the NMIHS data, we examined adequacy of weight gain and a variety of maternal and infant health outcomes, concentrating on whether differences existed between African-American and white women. We found evidence in this U.S. population-representative sample, numerous adverse maternal and child health outcomes were associated with either excess weight gain, obese pregravid BMI, or both. Research in this population was published in the appendix to the 2009 IOM report on pregnancy weight gain guidelines.

Literature Review

We focus on relating the functional predictor of pregnancy weight gain to the response of gestational age-adjusted birth weight. Clinicians and reproductive epidemiologists are interested in how the birth weight distribution for term births varies for women having different weight gain trajectories. To simplify clinical recommendations, it is useful to group women into different weight gain trajectory clusters, with the birth weight distribution possibly differing across clusters. Interest usually lies in the tails of the response distribution, such as small for gestational age birth weights, rather than the center of the distribution, measured by mean or median weight. To capture changes in tail behavior, it is important to allow the response
distribution to change flexibly across weight gain clusters. Our methods allow flexible inferences about any quantile of a distribution by allowing the response distribution to vary flexibly according to a functional trajectory predictor, avoiding dichotomization based on prespecified cut points, which is the current standard practice when primary interest lies in the tails of a distribution.

Growth and mixture modeling have been areas of rapid growth over the past thirty years (cf., Fitzmaurice et al. (2004); Diggle et al. (2002); Bollen and Curran (2006)). Methods based on finite mixture models that classify subjects into groups, first proposed by Rao (1958) and Tucker (1958) and refined by Meredith and Tisak (1984), McArdle (1988), McArdle and Epstein (1987), and Muthén (1991, 2004), have only recently been implemented in procedures compatible with SAS software (Nagin, 1999; Jones, Nagin, and Roeder, 2001; Nagin and Tremblay, 2001; Jones and Nagin, 2007). The Nagin approach, known as group-based trajectory modeling or latent class growth analysis, assumes that random effects characterizing subject-specific growth curves take one of $C$ distinct values, with $C \leq N$ representing the number of latent classes (or distinct values of latent growth curves). This approach, as well as the slightly more general Muthén approach, can be used to classify all $N$ women as having one of $C$ “typical” patterns of pregnancy weight gain.

It is important to avoid over-interpreting these latent trajectory classes as corresponding to clinically distinct subgroups, as the formation of clusters, using these methods, is dependent on parametric assumptions (Bauer and Curran, 2003). Instead, these existing methods should be viewed as a data reduction technique, and they aid in interpretation of the complex relationship between a functional predictor and response. In order to improve interpretability and avoid misleading inferences, we propose flexible methods that limit assumptions on the shapes of the trajectories, number of clusters, and conditional response distribution. Bayesian approaches are appealing in allowing one to borrow information adaptively across trajectory clusters to nonparametrically estimate cluster-specific response densities, while allowing for uncertainty in these estimates. Such borrowing of information is also critical in reducing uncertainty in estimation for the less common trajectory clusters, which are frequently those of most interest.

Bigelow and Dunson (2009) develop a Bayesian joint modeling approach, which first specifies component models for the functional predictor and a response, with these components linked through a joint distribution for the subject-specific coefficients. By assigning a Dirichlet process (DP) prior (Ferguson 1973, 1974) for this joint distribution, they obtain an unknown number of functional trajectory clusters. Unfortunately, in assigning a normal distribution for continuous outcomes within a trajectory cluster, their approach does not allow the tails or shape of the response density to vary across clusters. In addition, methods that assume a parametric response distribution within each cluster, such as the standard methods or the Bigelow and Dunson approach, have a clear tendency to over-estimate the number of trajectory classes when the parametric model does not provide an excellent fit. We propose an innovative new nonparametric Bayes approach that generalizes these methods to allow separate, but dependent, clustering in the predictor and response component models. This results in an unknown response distribution within each cluster, while adaptively borrowing information to an extent supported by the data. We avoid the need to select the number of clusters, specifying our model in terms of upper bounds, which can be infinity. We also develop a fast approach to computation, facilitating routine implementation. This new approach will lead to more flexible models, with better fit, and with more interpretable trajectory classes.

Another important statistical issue in latent class models is accounting for uncertainty in class assignment. Bayesian analysis of latent class or Gaussian mixture models poses several
challenges, such as selecting the number of components and the so-called label switching problem. The Bayes information criterion (BIC) is often used to choose the number of classes. For these models the BIC does not have a theoretical justification, and its continued use has been questioned in simulation studies. The non-identifiability of the components poses another hurdle; this happens when the parameters have exchangeable priors and permuting the labels of the parameters produces identical posterior distributions. One solution to this problem is to impose an identifiability constraint on the parameters, for example impose a particular ordering on the class means or precisions. We focus on developing latent class models for scenarios where information is available on several covariates, in addition to having a univariate response variable. We let the probability of belonging to a particular class depend on subject-specific covariates through a multinomial logit model. While one simpler alternative is to use probit regression for the underlying class probabilities, reproductive epidemiologists find logistic regression models more appealing, because the regression coefficients can be interpreted as the change in the log-odds of the binary response variable for an unit change in the predictors. In particular, it is of considerable interest to determine important predictors of the latent classes. We develop Bayesian variable selection methods for a novel formulation of multinomial logit regression models embedded in latent class models. If the latent classes were known the problem would boil down to incorporating variable selection uncertainty in logistic regression models for unordered categorical data, and we address both challenges in our work.

**Study Design and Methods**

**PIN Study**

The PIN Study was a prospective cohort examining risk factors for preterm birth and fetal growth restriction. Women were recruited from public and private prenatal clinics at the University of North Carolina Hospitals in Chapel Hill, North Carolina. Women younger than age 16, non-English speaking, not planning to delivery at the study site, or carrying multiple gestations were ineligible. Study staff recruited women at their second prenatal visit (mean gestational age 14 weeks) and before 20 weeks of gestation. Project staff explained the study, asked women to participate, and obtained signed consent from women who wished to enter the study. The study was approved by the UNC School of Medicine Institutional Review Board. PIN was the primary study used to examine trajectories of weight gain. In addition, a subset of women were followed in the PIN Postpartum and PIN Kids studies, allowing investigation of outcomes of postpartum weight retention and child weight for height at age 36 months. The proposed statistical methods for estimating trajectories of weight gain and health outcomes, along with more conventional methods, were used in analysis of the PIN data.

**National Maternal and Infant Health Survey (NMIHS)**

Data from the 1988 National Maternal and Infant Health Survey (NMIHS) and its 1991 longitudinal follow-up study were used to generate

- Descriptions of gestational weight gain distributions in the general population as well as in specific subgroups of interest
- Descriptions of distributions of pregnancy, birth, and maternal and child health outcomes, including gestational diabetes, pregnancy-induced hypertension, pre-eclampsia, c-section, preterm birth, birth weight among term births, small for gestational age, large for gestational age, breastfeeding initiation, duration of breastfeeding, postpartum weight retention, and childhood weight status
Results from statistical modeling of relationships between gestational weight gain, pregravid body mass index, and outcomes of interest

The primary advantages of using data from NMIHS are adequate power to study African-American women and the ability to explore relationships in a nationally-representative sample. Women included in the analysis had singleton pregnancies ending in live births as defined by NMIHS (NMIHS distinguishes live births from fetal and infant deaths). Due to the presence of numerous extreme outliers, data were cleaned by excluding (1) subjects with birth weights further than 3 standard deviations from the mean birth weight for each gestational age at delivery, (2) subjects with gestational weight gain greater than 40 kg or with gestational weight loss greater than -10 kg, and (3) deliveries before 26 weeks gestation nor after 42 weeks gestation. Due to poor quality of data on GDM, PIH, and pre-eclampsia, these outcomes were not analyzed in further detail.

Detailed Findings

PIN Study: Statistical Methodological Work on Incorporating Uncertainty in Model and Variable Subset Selection in Latent Class Models

One important aspect of latent class models often ignored is that there is uncertainty in class assignment due to positive probabilities of assignment to multiple classes. Another important concern for observational studies is the quantification of model uncertainty, due to use of selection techniques (e.g., stepwise selection methods or the “10% rule”) in determining an adjustment set of covariates (including potential confounders and effect modifiers). In Ghosh et al (2009), we developed methodology that allows estimation of latent classes while allowing for variable selection uncertainty. We proposed a Bayesian variable selection approach and implemented a stochastic search Gibbs sampler for posterior computation to obtain model averaged estimates of quantities of interest such as marginal inclusion probabilities of predictors. Our methods are illustrated through simulation studies and application to data on weight gain during pregnancy, where it is of interest to identify important predictors of latent weight gain classes.

Our model for weight gain, \( y_i \), for woman \( i \) follows the mixture of normals model below with \( w_i \) indicating the class membership, so that responses within a class are normally distributed. Class indicators follow a multinomial distribution with predictors (\( x_i \)) of class membership incorporated through a logistic function. The full list of predictors considered includes body mass index (underweight, normal weight, overweight, obese), maternal age (\( \leq 20, 21-29, 30-35, >35 \)), race (black versus not), depression (moderate and high symptom counts versus low counts), parity (nulliparous versus multiparous), percent carbohydrates in diet, percent fat in diet, percent protein in diet, total caloric intake, smoking (any versus none during pregnancy), maternal height, maternal diagnosis of gestational diabetes, physical activity (whether active in 3 months before pregnancy, in first trimester, and in 2nd trimester), and vomiting (significant vomiting or not). A model selection prior distribution is used to incorporate predictors of class membership, and other prior distributions are provided below, with complete details in Ghosh et al (2009).

Model Specification (See Ghosh et al., 2009, for full details):
Prior distributions:

\[ \mu_k \sim N(\xi, 1/\kappa), \quad \phi_k \sim G(\alpha, \beta), \text{ for } k = 1, \ldots Q \text{ and } \beta \sim G(g, h), \]

\[ \beta_k \sim \prod_{j=1}^P \left\{ p_{kj} \delta_k(\beta_{kj}) + (1 - p_{kj})N(\beta_{kj}; 0, \sigma_{kj}^2) \right\}, \quad k = 1, 2, \ldots (Q - 1), \]

Table 1 shows the estimated beta coefficients and posterior probabilities that predictors of interest impact weight gain class assignment. Underweight women tended to fall into the moderate class with high probability whereas overweight and obese women tended to be in the low class, providing evidence that women are following weight gain recommendations. Black women or those with depressive symptoms tended to be in the low gain class. Nulliparous women tended to be in the high gain class, and women with higher percent protein in their diets were more likely to be in the high and moderate classes than in the low weight gain class. The posterior distributions of mean weight gain rate by weight gain class are given in Figure 1, showing nice separation of the mean weight gain rate across the different classes.

| Predictor    | \( E(\beta_{1j}|Y) \) | \( \hat{P}(\beta_{1j} \neq 0|Y) \) | 95% C.I. | Predictor    | \( E(\beta_{2j}|Y) \) | \( \hat{P}(\beta_{2j} \neq 0|Y) \) | 95% C.I. |
|--------------|------------------------|-----------------------------|---------|--------------|------------------------|-----------------------------|---------|
| Intercept    | 1.1                    | 1                           | (0.57 , 1.82) | Intercept    | 1.82                   | 1                           | (0.93 , 2.56) |
| bmi class 3  | -0.67                  | 0.83                        | (-1.45 , 0 ) | bmi class 1  | 1.66                   | 1                           | (0.95 , 2.62) |
| bmi class 4  | -2.19                  | 0.97                        | (-2.79 , -1.64 ) | bmi class 3  | -0.8                   | 0.87                        | (-1.61 , 0 ) |
| race black   | -0.77                  | 0.97                        | (-1.29 , 0 ) | bmi class 4  | -3.31                  | 1                           | (-4.06 , -2.61 ) |
| parity 0     | 0.85                   | 1                           | (0.46 , 1.27 ) | mage <= 20   | -0.7                   | 0.88                        | (-1.43 , 0 ) |
| pct prot     | 0.25                   | 0.8                         | (0.0 , 0.54 ) | mrace black  | -0.94                  | 0.98                        | (-1.5 , -0.28 ) |
| no smoke     | -0.56                  | 0.86                        | (-1.14 , 0 ) | cesat 3      | -0.68                  | 0.88                        | (-1.39 , 0 ) |
| height       | 0.67                   | 1                           | (0.46 , 0.91 ) | pct prot     | 0.31                   | 0.84                        | (0 , 0.63 ) |
Table 2: Associations between pregravid BMI, weight gain class, and birth weight (in kg).

Table 2 shows relationships we identified with birth weight. It is evident that overweight (bmiclass3) and obese (bmiclass4) women had heavier babies than underweight or normal weight women. For example, obese women with low weight gain had babies on average 160 (60, 260) g heavier than those of their normal weight counterparts. For a complete picture of the interaction effects of pregravid BMI and weight gain classes on the infant birth weight, see Figure 2, which plots the estimated association as a function of gestational age. Figure 3 plots the same associations, grouping by pregravid BMI categories instead of latent classes. Birth weight was on average 170 (120, 200) g greater for nonsmokers, 170 (140, 210) g less for nulliparous women, and 110 (80, 140) g heavier for male infants.
Figure 2: Estimated birth weight as a function of pregravid BMI and weight gain class, holding other covariates at most commonly observed values (non-smoker, nulliparous, white mother of male infant), grouped by weight gain class (high, moderate, low).

Figure 3: Estimated birth weight as a function of pregravid BMI and weight gain class, holding other covariates at most commonly observed values (non-smoker, nulliparous, white mother of male infant), grouped by pregravid BMI.

PIN Study: Statistical Methodological Work on Developing New Statistical Methods for Estimation of Partially-Stratified Trajectories of Weight Gain and Health Outcomes
A second major aim of the work was to extend preliminary work on estimation of weight gain trajectories and relationships with birth weight to accommodate stratified estimation by pregravid BMI. A major challenge encountered during implementation of this aim was the limitation of the PIN sample size when estimating latent trajectories in some of the smaller weight gain groups, such as underweight or overweight. Initial work indicated that trajectories estimated for normal weight women (Figure 4) may not be the same as those in other pregravid groups (see Figure 5).

Using this fully-stratified estimation of trajectories, there is insufficient capability for testing whether the estimated trajectories are the same or not for these underweight and normal weight women. Thus after extensive testing of the proposed methods, we have decided that a more appropriate approach is to consider partial stratification, in which a common set of trajectories is estimated across all pregravid BMI classes, and then a separate group of pregravid BMI-specific trajectories is introduced as needed. This allows a straightforward method of testing whether trajectories of weight gain are common across all BMI categories or whether some trajectories are common only to one or a couple of pregravid BMI groups. Statistical properties of our proposed methods are promising but still under investigation; in Cornea et al. (2009), we are exploring these properties, and we will submit an additional publication to the reproductive epidemiology literature relating the estimated trajectories to the full range of birth outcomes of interest.

Figure 4: Estimated trajectories and membership percentages for normal weight women

PIN Study: Examining the Determinants of Gestational Weight Gain

A number of manuscripts have been completed that examine predictors of gestational weight gain. In Mumford et al. (2008), we found associations between restrained eating behaviors and
gestational weight gain. In particular, restrained eating behaviors were associated with higher than adequate weight gains for normal, overweight, and obese women, while they were associated with lower than adequate weight gains for underweight women. Women classified as “cyclers” gained an average of 2 kg more than non-cyclers and showed higher ratios of observed to expected weight gains. These results have been published in the *Journal of the American Dietetic Association*.

![Figure 5: Estimated trajectories and membership percentages for underweight women](image)

In Deierlein et al. (2008), we found that dietary energy intake, but not glycemic load, was associated with gestational weight gain. After adjustment for covariates, compared with women in the first quartile consuming a mean dietary energy density of 0.71 kcal/g (referent), women in the third quartile consuming a mean energy density of 0.98 kcal/g gained an excess of 1.13 (0.24, 2.01) kg, and women in the fourth quartile consuming a mean energy density of 1.21 kcal/g had an increase of 0.13 (0.01, 0.24) units in the observed:expected weight gain ratio.

In Mehta et al (2009), we found that body image influenced gestational weight gain in a complex manner. Race, education, and income were found to modify the relationship between body image and weight gain. Low income women preferring a light body size over an average size had increased risk of gaining inadequately during pregnancy [RR=1.76 (95% CI: 1.08, 2.88)]; women with lower education preferring a light versus average size were at higher risk of gaining excessively [RR=1.11 (95% CI: 1.00, 1.23)]. African American women who preferred a heavy body size gained significantly less weight than African American women preferring an average
size [-3.45 kg (95% CI:-6.88, -0.01)]; there was no effect of preferring a heavy versus average body size for Caucasian women [2.6 kg (95% CI:-0.35, 5.56)].

**PIN Study: Examining Other Consequences of Gestational Weight Gain**

In Siega-Riz et al. (2009), we examined the relationship between pregnancy weight gain and postpartum weight retention. The average weight retained at 3 and 12 months in this population was 9.4 lbs (SD=11.4) and 5.7 lbs (SD=13.2) respectively. At 3 months postpartum, prepregnancy weight, gestational weight gain, and hours slept during the night were associated with moderate or high weight retention while having an infant hospitalized after going home and scoring in the upper 75th percentile of the eating attitudes test were associated with high weight retention. At 12- months postpartum, prepregnancy weight, gestational weight gain and maternal education were associated with moderate weight retention; and gestational weight gain, maternal age, race, employment status, and having an infant hospitalized at birth were associated with high weight retention. The results of this study clearly point to the importance of prepregnancy weight and gestational weight gain in predicting postpartum weight retention. Furthermore, given the lack of successful intervention studies that exist to date to help women lose weight in the postpartum period, the results of this study may help to inform future interventions that focus on such aspects as hours of sleep, dealing with stress associated with a hospitalized infant and non-clinical eating disorder symptomatology. In preliminary work on child BMI, we are finding evidence of an interaction between pregravid BMI and adequacy of weight gain on children’s weight for height z-scores at age three. We plan to submit a manuscript based on this work in Spring 2010. In addition, a comprehensive manuscript on statistical methods for estimating exposure trajectories and a comprehensive set of maternal and child outcomes will also be submitted in Spring 2010.

**NMIHS: Investigation of weight gain adequacy and host of maternal and child health outcomes**

The original gestational weight gain variable in NMIHS had mean 30.5 pounds and ranged from 21.7 pounds lost to 235 pounds gained. For purposes of this analysis, data were cleaned by excluding the top 1% and bottom 1% of this variable. The resulting variable had range limited to 22 pounds lost to 79 pounds gained. Twenty-nine percent of women had inadequate gain; 26 percent of women had adequate gain, and 45 percent of women had excessive gain based on the 1990 IOM recommendations for weight gain and NHLBI cutoffs for BMI.

Weight gain adequacy was related to pregravid BMI category, as described below in Table 3. In particular, underweight women tended to have inadequate or adequate gain, while the majority of normal weight, overweight, and obese women had excessive gain. Interestingly, fewer overweight women had inadequate gain than women in any other group.

<table>
<thead>
<tr>
<th>Pregravid BMI</th>
<th>Inadequate</th>
<th>Adequate</th>
<th>Excessive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underweight</td>
<td>33.7%</td>
<td>41.2%</td>
<td>25.1%</td>
</tr>
<tr>
<td>Normal</td>
<td>29.8%</td>
<td>28.7%</td>
<td>41.5%</td>
</tr>
<tr>
<td>Overweight</td>
<td>19.4%</td>
<td>18.8%</td>
<td>61.8%</td>
</tr>
<tr>
<td>Obese</td>
<td>32.9%</td>
<td>7.7%</td>
<td>59.5%</td>
</tr>
</tbody>
</table>

Figure 6 provides a summary of probabilities of various outcomes as a function of weight gain adequacy and pregravid BMI in the NMIHS data. All analyses we first conducted stratified on race, though race was a significant effect modifier only for SGA and LGA outcomes, so that
stratification by race was retained only in these models. As illustrated in Figure 6, risk of SGA was greatest for underweight women and for women gaining inadequate weight; risk of LGA was highest for obese women and for women who gained excessively; PTB risk was unrelated to weight and weight gain; risk of C-section was greatest for those who gained excessively and for overweight or obese women; breastfeeding initiation rates were greatest for those with adequate weight gain and lower for women gaining outside the recommended ranges, and postpartum weight retention over 5 kg was greater for women who gained adequately or excessively and for overweight or obese women, with particularly high retention rates for women who were both obese and gaining excessively. This and other related work is published in the appendix to the 2009 IOM report on reevaluation of the pregnancy weight gain recommendations.

Figure 6: Risks, by NHLBI BMI and IOM weight gain (inadequate, adequate, excessive) categories, of SGA, LGA, PTB, c-section, breastfeeding initiation (BFINIT), breastfeeding 6 months among initiators (BF6), and postpartum weight retention > 5kg (PP5).
Discussion and Interpretation of Findings

As part of our work, we developed novel methods for quantification of class assignment uncertainty in general latent class models, applying them to the study of gestational weight gain and birth weight. These methods will help investigators avoid uncertainty in assignment of the number of latent classes whenever such methods are used. A second major aim of the work was to extend preliminary work on estimation of weight gain trajectories and relationships with birth weight to accommodate stratified estimation by pregravid BMI. A major challenge encountered during implementation of this aim was the limitation of the PIN sample size when estimating latent trajectories in some of the smaller weight gain groups, such as underweight or overweight. Initial work indicated that trajectories estimated for normal weight women may not be the same as those in other pregravid groups. However, using this fully-stratified estimation of trajectories, there is insufficient capability for testing whether the estimated trajectories are the same or not for these underweight and normal weight women. We now are developing a new, straightforward method of testing whether trajectories of weight gain are common across all BMI categories or whether some trajectories are common only to one or a couple of pregravid BMI groups. Statistical properties of our proposed methods are promising but still under investigation.

Areas for ongoing statistical development include additional methods for selecting the number of latent classes in latent class models (particularly from the frequentist perspective) and for handling issues related to label switching in Bayesian models.

As part of our work, we identified several other areas worthy of further scientific development. In particular, despite a note in the 1990 IOM report that research on consequences of pregnancy weight gain in minority populations should be carried out, we found no large, population-representative U.S. cohorts with substantial minority participations more recent than the 1988 NMIHS study. Additional research is warranted for the study of health effects of weight gain in multiple minority groups, including Hispanic and black women.

Peer-reviewed articles


**Conference presentations and invited talks**

“Assessing Impact of Longitudinal Predictors on Changes in Response Densities: Does Amount and Timing of Pregnancy Weight Gain Affect Birth Weight?” University of Georgia, November 2009


“Latent class models for characterizing complex predictors in epidemiologic studies,” Research Triangle Institute, July 2009

“Bayesian Inference on Changes in Response Densities over Predictor Clusters,” Harvard University, April 2009

“Assessing Impact of Longitudinal Predictors on Changes in Response Densities: Does Amount and Timing of Maternal Weight Gain in Pregnancy Affect Birth Weight?” University of Michigan, April 2009

“Bayesian Inferences on Changes in Response Densities over Predictor Clusters,” Vanderbilt University, January 2009

“Bayesian Inferences on Changes in Response Densities over Predictor Clusters,” NIH (NCI), December 2008

“Bayesian Inferences on Changes in Response Densities over Predictor Clusters,” University of Bocconi, Milan, Italy, November 2008

“Joint Models for Pregnancy Weight Gain Patterns and Health Outcomes,” NIH (NIEHS), October 2008

**Master’s and doctoral dissertations**

Cornea, E. Semiparametric Bayesian joint models for relating functional trajectories and health outcomes. In progress.

Deierlein, A. Association between gestational weight gain and child weight status at age 3, rapid infant weight gain, and child growth trajectories. In progress.
References


