Response to Invited Commentary

Terry et al. Respond to “Antecedents of Obesity”

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The commentary by Drs. Gillman and Kleinman (1) on our paper examining pre- and postnatal predictors of adult body mass index (BMI) (2) highlights the analytic and design challenges of conducting these types of investigations.

Choice of model

We agree with Gillman and Kleinman that employing a variety of analytic approaches illuminates the sensitivity of findings to model specification. We compared standard analytic approaches (ordinary linear and logistic regression) with quantile regression. Logistic regression and its generalization, multinomial (polytomous) regression, estimates the covariate effect on the risk of exceeding a prespecified threshold determined by the marginal distribution of the outcome (3). These techniques are useful for applications in which a natural cutoff value exists (4, 5). In our case, sparse cell counts at suggested cutoff points (>30 kg/m², <18.5 kg/m²) limited meaningful polytomous modeling. Quantile regression does not rely on prespecified thresholds; rather, it examines how the conditional distribution of the outcome varies with the covariates (6). While all three statistical models in our study supported associations between maternal, infant, and early-life factors and adult BMI, quantile regression allowed for additional inferences regarding the relative magnitudes of the associations for smaller, average, and larger women.

Exposure construct

Although we considered alternative exposure constructs, we selected percentile changes because our interest was in the impact of percentile rank changes relative to constant percentile rank (growth trajectory) on adult BMI. We found similar associations, however, when modeling z score differences. In models based on absolute weight measures, rather than rates, weight at age 7 years was the only postnatal measure associated with adult BMI. This was probably due to the strong positive correlation in absolute measures over time as opposed to the weaker and negative correlation in growth rates. The negative correlation between birth weight and postnatal growth rates means that few high birth weight babies increase in percentile rank; however, those that do have a higher BMI in adulthood, as our final models suggest.

Model-building

Although we used standard progressive modeling (table 2) to assess potential mediation, we recognize that these methods may be limited in the presence of confounding and interaction (7). We also used path modeling (8) to assess mediation but did not fully explore its multivariate regression extension—structural equation modeling (9)—because it relies on modeling the mean level. Both quantile regression and path analyses confirmed that all of the variables included in our final model were independent predictors.

Design challenges

We were fortunate to build upon data from the New York City site of the National Collaborative Perinatal Project, which prospectively collected pre- and postnatal data on offspring up to the age of 7 years (10). We agree that clinical evaluations of anthropometric factors are necessary to explore plausible biologic explanations for these associations; however, given the geographic diversity of the adults in our study, we were limited to questionnaire data on body size.
Empirical evaluation of human life-course questions will always rely on piecing together information from multiple lines of evidence and multiple time periods. Rejuvenating the National Collaborative Perinatal Project cohort and similar birth cohorts may be an efficient first step (11).

Data inference

Gillman and Kleinman (1) argue that targeting interventions to the more narrow pregnancy window may ultimately prove more efficient for obesity prevention. Although our models suggested that maternal weight gain may be one important feature, other variables such as childhood weight gain and maternal BMI remained associated with BMI at age 40 years. The overall fit of the model was based on the collection of variables and not any single variable. Limiting pregnancy weight gain may result in many adverse outcomes, including lower birth weight among babies, who then may be at risk of obesity from rapid postnatal growth. Continued focus on maintaining a healthy BMI throughout life, however, will improve a woman’s own health and may ultimately prove to influence her offspring’s.

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REFERENCES