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Maternal dietary patterns are associated with lower levels of cardiometabolic markers during pregnancy

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Abstract

Background—Elevated levels of cardiometabolic markers are characteristic of normal pregnancy; however, insulin resistance and increased glucose, triglyceride, and cholesterol levels can adversely influence maternal and child health. Diet is a modifiable behavior that could have significant impact on maternal cardiometabolic levels during pregnancy. We investigated the association between dietary patterns and cardiometabolic markers (glucose, insulin, insulin resistance (HOMA-IR), triglycerides, and cholesterol) during pregnancy.

Methods—Data from the Pregnancy, Infection, and Nutrition prospective cohort study (2000-2005) was used (n=513). Diet was assessed using a food frequency questionnaire. Dietary patterns were derived using latent class analysis (LCA) and the Dietary Approaches to Stop Hypertension (DASH) diet. Linear regression was used to examine the dietary patterns-cardiometabolic markers association during pregnancy.

Results—Three dietary patterns evolved from the LCA characterized by high intakes of: 1) hamburgers, hot dogs, bacon, French fries, fried chicken, white bread, and soft drinks; 2) some vegetables, fruit juice, refined grains, mixed dishes, processed meat, and empty calorie foods; and 3) fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water. After adjustment for potential confounders including pre-pregnancy body mass index, a diet consistent with Latent Class 3 was negatively associated with maternal insulin (μU/mL: β=−0.12; 95% CI: −0.23, −0.01)

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and HOMA-IR (β=−0.13; 95% CI: −0.25, −0.00). Additionally, DASH scores within Tertile 3 (higher dietary quality) were also negatively associated with maternal triglycerides (mg/dL).

Conclusions—The study findings suggest an association between maternal dietary patterns and several cardiometabolic markers during pregnancy.

During a typical pregnancy, several metabolic adaptations occur to sustain pregnancy and promote fetal growth and development.[1-2] Higher levels of several cardiometabolic markers are characteristic of a normal pregnancy; however, several studies have shown that insulin resistance, as well as, increased glucose, triglyceride, and cholesterol levels are associated with adverse maternal and child outcomes,[3-7] creating a need for studies that identify factors during pregnancy that have favorable effects on cardiometabolic markers.

Maternal diet during pregnancy is one potential modifiable behavior that could significantly impact cardiometabolic levels. Unfortunately, studying diet is not straightforward as people do not eat foods and nutrients in isolation. Instead, foods and nutrients are eaten in combination, which likely have interactive and synergestic effects.[8] To address this, dietary patterns are commonly used as measures of overall diet quality. Dietary patterns are primarily defined using score-based and data-driven approaches.[8] Score-based methods are based on dietary recommendations or substantive knowledge of specific diseases and scores are assigned at the individual-level to reflect adherence. Data-driven methods use statistical approaches to derive major dietary patterns in a population independent of their relationship to a disease.

The influence of dietary patterns on cardiometabolic markers has been described in studies of healthy non-pregnant individuals using both score-based and data-driven methods.[9-11] However, less is understood during pregnancy when changes in metabolic profiles are typical. Studies in pregnant women have mainly included small sample sizes, racially homogenous study populations, and pregnant women with gestational diabetes.[12-15] One previous study found a negative correlation between the Mediterranean-style diet and fasting glucose during pregnancy.[15] Unfortunately, other important cardiometabolic markers were not examined. In this study, we sought to investigate cardiometabolic markers during pregnancy as they relate to maternal dietary patterns using both a score-based and data-driven approach.

METHODS

Study design and population

We used data from the third cohort of the Pregnancy, Infection, and Nutrition study, which recruited women from private and public prenatal clinics at the University of North Carolina Hospitals to participate in a prospective study investigating risk factors of preterm birth.[16] Pregnant women ≤20 weeks' gestation, 16 years of age and older, carrying singleton gestation, with telephone accessibility, and planning to continue care at the same clinic were recruited to participate from January 1, 2001 to June 30, 2005 and followed to delivery. Women provided written informed consent at recruitment and all procedures were reviewed and approved by the UNC Institutional Review Board.

A total of 1,875 pregnant women (2,006 pregnancies) were enrolled, of which 1,352 women (1,442 pregnancies) had complete dietary information. Because it was possible for a woman to have multiple pregnancies during the study, we randomly selected one pregnancy per woman from those with complete dietary information to be included in this analysis. A new study protocol was later funded that included fasting blood draws. Of those eligible, 967 women agreed to participate and provide fasting blood samples. Seven hundred twenty-one women had blood samples at each of the two research visits. Thirty-seven women had only one blood sample drawn, while 209 women, despite being eligible for and consenting to the blood draw protocols, had no blood samples drawn. We included women who had biomarker data for all cardiometabolic markers of interest (fasting glucose, insulin, total cholesterol, and triglycerides; n=569). We compared maternal characteristics to determine whether women with data for all cardiometabolic markers (n=569) differed from women excluded (n=783). Women with complete biomarker data had a slightly lower mean ± SD pre-pregnancy body mass index (BMI; 25.3 ± 6.5 kg/m^2) than women excluded (26.2 ± 7.3 kg/m^2; P<0.01). No other significant differences were found. We further excluded women with pre-existing diabetes (n=12), chronic hypertension (n=34), or both conditions (n=10) because it is possible that these women received preconception dietary advice for their conditions, which could have influenced their dietary habits during pregnancy, resulting in 513 women in this analysis.

Assessment of primary outcomes

Fasting blood samples were collected at 26-29 weeks gestation. Glucose (mg/dL) and insulin (μU/mL) were both assayed by LINCO Research, Inc. using a standard hexokinase method and double antibody/PEG technique. Using nuclear magnetic resonance technique (NMP LipoProfile®), cholesterol (mg/dL) and triglycerides (mg/dL) were assayed by LipoScience, Inc. We estimated insulin resistance from glucose and insulin using the homeostasis model for assessment of insulin resistance (HOMA-IR).[17-18]

Assessment of primary exposures

Information on diet was collected at 26-29 weeks gestation using a self-administered, semi-quantitative, 119-item Block food frequency questionnaire (FFQ) to assess dietary intake over the previous three months. The FFQ was validated in the PIN study by comparing nutrient results with three 24-hour dietary recalls collected on random nonconsecutive days from 99 women. Details of the validation are provided elsewhere.[19] To calculate daily energy intake (kcals) and grams per day, we used Dietsys+Plus version 5.6 with an updated food composition table based on nutrient values from the NHANES III and USDA 1998 nutrient databases.

We examined dietary patterns using a score-based and a data-driven approach. The Dietary Approaches to Stop Hypertension (DASH) diet was the score-based method used. [20] It was previously shown to positively influence metabolic profiles in pregnant women.[12-13] The DASH scoring method was based on a previously developed approach, where participants received points based on their quintile of intake for 8 food components.[21] In brief, intake of fruits, vegetables, nuts and legumes, low fat dairy, and whole grains were assigned one point for each successive quintile ranking (e.g. lowest quintile = 1 point, highest quintile = 5 points). Sodium, red and processed meat, and sweetened beverage intakes were reverse scored, giving the lowest quintile of intake five points and the highest quintile one point. DASH scores were computed by summing the 8 DASH component scores and could range from 8 (not adherent) to 40 (adherent). We divided DASH scores into tertiles for all analyses where the highest tertile represented healthier diet quality.

Latent class analysis (LCA) was used to derive data-driven dietary patterns. The methodology for LCA is described in full detail elswhere.[22-23] The number of FFQ food items was reduced from 119 to 105 due to the exclusion of rarely consumed food items (< 10%) and combining low-fat milks (skim, 1%, and 2%) into one group because of small cell counts. Because many of the food items had skewed distributions due to high prevalence of non-consumers, we used categories of intake. Food items with a high prevalence of consumption (non-consumption <10%; n=17 items) were dichotomized at the median. Food items with a low prevalence of consumption (non-consumption >70%; n=8) were dichotomized as consumed vs. non-consumed. The remaining food items (n=80) were categorized into three levels: non-consumers, below the median among consumers, and above the median among consumers. We fit energy-adjusted LCA models with 2 to 4 classes and used Lo-Mendell-Rubin likelihood ratio test (LRT) to determine the number of classes. Women were classified into mutually exclusive classes according to their highest predicted probability of class membership.[24]

Covariates

At enrollment, women reported their age, race, marital status, parity, household income, education level, pre-pregnancy weight, smoking status, and physical activity via telephone interviews. Physical activity over the past seven days was recorded at 17-22 weeks' gestation. The frequency and duration of all moderate and vigorous occupational, recreational, household, child and adult care, and transportation activities were assessed. Perceived intensity was assessed using the Borg scale.[25] Total metabolic equivalent (MET) hours per week were calculated. Pre-pregnancy BMI was calculated based on self-reported pre-pregnancy weight (kilograms) and height (meters squared), which was measured at the first clinic visit. Missing or implausible pre-pregnancy weights were imputed using weight at first prenatal care visit for 3.7% of the study population. Self-reported weight was highly correlated with measured weight in pregnant women in previous research (r=0.98).[26] BMI classifications followed the 2009 Institute of Medicine recommendations: underweight <18.5 kg/m^2; normal weight 18.5-24.9 kg/m^2; overweight 25.0-29.9 kg/m^2; and obese ≥30.0 kg/m^2.

Statistical analysis

To avoid excluding women with missing covariate information from the analysis, we used data from our three months postpartum survey for missing federal poverty level (n=12) and smoking status (n=9). We used multiple imputation methods to estimate values of other missing covariate data for maternal race (n=1), prenatal smoking (n=18), and federal poverty level (n=20). All covariates and outcomes discussed previously were included in the multiple imputation models.[27] We used 10 iterations to produce 10 imputed datasets for regression analyses and parameter estimates were summarized.[27]

We summarized maternal demographic, behavioral, dietary, and cardiometabolic characteristics by dietary patterns using percentages for categorical variables and means and standard deviations (SDs) for continuous variables. All cardiometabolic markers with non-normal distributions were transformed using natural logarithms. Statistical significance was evaluated using χ^2 and Analysis of Variance (ANOVA) tests for categorical and continuous variables, respectively ($P<0.05$).

The relationship between maternal dietary patterns and cardiometabolic markers during pregnancy was assessed in a series of linear regression models: (1) examining the associations of dietary patterns alone; (2) adjusted for maternal age, race, poverty level, parity, smoking status, physical activity, and energy intake; and (3) further adjusted for continuous pre-pregnancy BMI. Confounding was determined using directed acyclic graphs.[28] Other covariates (maternal education and marital status) were tested as potential confounders, but were not included because they did not meaningfully influence our estimates (change-in-estimate <10%).[29] We also tested for interaction between maternal pre-pregnancy BMI and dietary patterns using Wald tests ($P<0.15$). To determine the influence of implausible energy intake, we performed sensitivity analyses excluding women with daily kcals above and below ±1st, ±2.5th, and ±5th percentiles. Statistical analyses were performed using SAS version 9.3 (SAS Institute, Inc. Cary, NC) and Mplus Version 7.3 to fit the latent class models.

RESULTS

The LCA identified three latent classes. Class 1 was characterized by high intake of hamburgers, hot dogs, French fries, fried chicken, white bread, bacon, and soft drinks (n=150). Class 2 was characterized by high intake of some vegetables, refined grains, mixed dishes, meat, poultry, processed meat, salty snacks, sweets, some fast foods, and fruit juice (n=163). Class 3 included high intake of fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water (n=200).

DASH scores ranged from 12 to 37 with a mean of 24.2 ± 5.1. There were 36.2% of women with DASH scores within Tertile 1 (score range: 12-22), 35.5% within Tertile 2 (score range: 23-27), and 28.3% within Tertile 3 (score range: 28-37). Maternal demographic and behavioral characteristics by DASH score tertile and latent class are given in Table 1. On average, women in DASH Tertile 3 and Latent Class 3 were older, more likely to be non-Black and married, had a lower prevalence of pre-pregnancy obesity and smoking during pregnancy, and more likely to have higher household income (>350% federal poverty level) and more than a college education (≥ Grade 17).

By design, women with DASH scores in the highest tertile had higher consumption of healthy food items (i.e. fruits, vegetables, whole grains, etc.) and lower consumption of unhealthy foods (i.e. red meat, sweetened beverages, etc.) compared to women with scores in the lower tertiles (**Table 2**). Women grouped into Latent Class 3 had higher mean intake of vegetables, whole grains, and low fat dairy, and lower intake of red meat and sweetened beverages than women in the other classes. Saturated fat intake was also lower for women categorized into DASH Tertile 3 and Latent Class 3.

Results from linear regression analyses are provided in Table 3. DASH Tertile 1 and Latent Class 1 were denoted as the reference categories for DASH and LCA models, respectively. In models adjusted for maternal age, race, poverty level, parity, smoking status, physical activity, and energy intake (Model 2), DASH Tertile 3 scores were negatively associated with insulin, insulin resistance, and triglycerides. A diet consistent with Latent Class 3 was positively associated with glucose, insulin, and insulin resistance. After further adjustment for pre-pregnancy BMI (Model 3), the negative associations of insulin, insulin resistance, and triglycerides with DASH Tertile 3 and the negative associations of insulin and insulin resistance with Latent Class 3 were slightly attenuated. We did not find evidence of interaction between maternal prepregnancy BMI. Associations were similar after excluding women with daily energy intakes ±1st percentile (770 and 5010 kcals), ±2.5th percentile (995 and 4337 kcals), and ±5th percentile (1106 and 3668 kcals).

COMMENTS

Our results suggest that adherence to a healthier dietary pattern during pregnancy is associated with lower cardiometabolic markers during pregnancy. Specifically, we found that higher DASH scores were associated with lower maternal insulin, HOMA-IR, and triglycerides. Similarly, a dietary pattern characterized by high consumption of fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water was associated with lower maternal glucose, insulin, and HOMA-IR. Associations were slightly attenuated upon further adjustment for pre-pregnancy BMI; however, several significant associations remained.

Studies of maternal dietary patterns and cardiometabolic markers during pregnancy are sparse. We are aware of only four previously published studies.[12-15] Our findings of an association between healthier dietary patterns and cardiometabolic levels during pregnancy were generally consistent with results from a small RCT of women with gestational diabetes.[12] Women with diagnosed gestational diabetes randomized to the DASH diet at 24-28 weeks of gestation, as opposed to a control diet (40-55% energy as carbohydrates, 10-20% as proteins, 25-20% as fats), observed significant decreases in fasting insulin and HOMA-IR after the four-week study period.

We observed a negative association between higher DASH scores and fasting glucose; however, after additional adjustment for pre-pregnancy BMI the association no longer remained. Similarly, Asemi et al found no association between the DASH diet and fasting glucose in the RCT.[13] Karamanos et al. found a significant negative correlation between the Mediterranean-style diet and fasting glucose in women without gestational diabetes; however, the correlation was not adjusted for several important confounding factors.[15] Unlike previous RCTs, we did not find an association between dietary patterns and total cholesterol.[13,14]

Although the mechanisms explaining associations between maternal dietary patterns and insulin, HOMA-IR, and triglyceride levels are unclear, the results are biologically plausible. The healthier dietary patterns (DASH Tertile 3 and Latent Class 3) have higher intakes of fruits, vegetables, and whole grains, which are rich sources of antioxidants, phytochemicals, Vitamin C, and dietary fiber, and may contribute to the protective associations seen in this study. In a previous study, Vitamin C was inversely associated with the risk of gestational diabetes.[30] Women in DASH Tertile 3 and Latent Class 3 also had lower consumption of red and processed meats. High intakes of red and processed meats increased the risk of insulin resistance and gestational diabetes in previous studies likely due to high concentrations of saturated fat, heme iron, and nitrosamines in the diet.[31] Women with healthier dietary patterns are also likely to gain less weight during pregnancy, which is a risk factor for insulin resistance during pregnancy;[32-33] however, we did not account for gestational weight gain in our adjusted models because it is on the causal pathway between diet quality and cardiometabolic markers.

Dietary patterns are commonly used as measures of overall diet quality. Unlike single food and nutrient studies, dietary patterns have the advantage of capturing the combinations of foods eaten together, which are more applicable to clinical and public health settings. Although score-based and data-driven methods describe the overall diet, the methodology of each results in different characterizations. Score-based methods, like the DASH diet, are based on dietary guidelines and substantive knowledge. This method is useful in quantifying the overall healthiness of the diet in a population.[8] Data-driven methods, like LCA, describes the populations eating behaviors.[8] A disadvantage of data-driven methods is the difficulty in making comparisons across research studies, as the dietary patterns derived are often specific to the study population.[34-35] As such, we used descriptions of the foods consumed in each pattern instead of naming the identified patterns. By identifying the foods, we were able to identify similar dietary patterns from the two approaches and relationships with cardiometabolic markers, which speaks to the robustness of the associations between dietary patterns and the outcomes examined.

Although we were able to adjust for several potential confounding factors, we cannot dismiss the possible influence of unmeasured confounding. Two potential confounders that we did not have information on were preconception dietary patterns and hormonal status during pregnancy. Dietary intake was assessed using a single FFQ administered at 26-29 weeks gestation to represent intake in the previous three months. Based on results from previous research dietary patterns change minimally, if any, during pregnancy from the preconception period.[36] Hormonal status during pregnancy plays an important role in fluctuations of lipids and glucose during pregnancy.[37-39] Maternal BMI may alter circulating concentrations of metabolic hormones during pregnancy, which, in turn, influence nutrient transport capacity.[39] To address this limitation, we included pre-pregnancy BMI in the fully adjusted regression models to account for possible variations in the maternal diet-cardiometabolic markers association that may be explained by preconception diet and hormonal status. We also recognize the potential for residual confounding, as DASH scores in the bottom tertile were related to lower education and income levels, as well as higher proportions of pre-pregnancy obesity and smoking during pregnancy, while DASH scores in the top tertile were related to higher education and income levels and lower proportions of pre-pregnancy obesity and smoking during pregnancy. Lastly, women included in our study received prenatal care at a single University-based hospital system and resulted in a sample with high income and education, which may limit the generalizability of our study results.

Despite the limitations, our results suggest a relationship between maternal dietary patterns and cardiometabolic markers during pregnancy. Although our effect sizes were small, we did observe an inverse association between diet quality and maternal insulin, HOMA-IR, and triglyceride levels, which are important factors for maternal and offspring health. Our study used two approaches to characterize diet quality and the underlying food components were similar—fruits, vegetables, whole grains, low fat dairy, which is consistent with the US Dietary Guidelines for Americans. The findings of our study have important implications, as healthy diet is an established predictor of better health. Future studies with larger sample sizes in a more diverse population are needed to confirm our findings.

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Table 1

Distribution of maternal characteristics by DASH score tertile or latent dietary class, Pregnancy, Infection, and Nutrition (PIN) study, (n=513)

	DASH[a]			Latent Dietary Class[b]		
Variable[c]	Tertile 1 (n= 186)	Tertile 2 (n=182)	Tertile 3 (n=145)	Class 1 (n=150)	Class 2 (n=163)	Class 3 (n=200)
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
Age (years)						
16-24	70 (37.6)	35 (19.2)	11 (7.6)	58 (38.7)	49 (30.1)	9 (4.5)
25-29	50 (26.9)	60 (33.0)	35 (24.1)	52 (34.7)	40 (24.5)	53 (26.5)
30-34	44 (23.7)	61 (33.5)	72 (49.7)	27 (18.0)	53 (32.5)	97 (18.5)
35-47	22 (11.8)	26 (14.3)	27 (18.6)	13 (8.7)	21 (12.9)	41 (20.5)
Race						
Non-Black	135 (72.6)	158 (86.8)	137 (95.1)	111 (74.0)	125 (76.7)	194 (97.5)
Black	51 (27.4)	24 (13.2)	7 (4.9)	39 (26.0)	38 (23.3)	5 (2.5)
Marital status						
Married	114 (61.3)	150 (82.4)	133 (91.7)	91 (60.7)	118 (72.4)	188 (94.0)
Unmarried	72 (38.7)	32 (17.6)	12 (8.3)	59 (39.3)	45 (27.6)	12 (6.0)
Family income (% federal poverty level)						
<185%	61 (43.3)	25 (14.5)	9 (6.4)	45 (33.6)	39 (24.4)	11 (5.6)
185-350%	40 (22.5)	42 (24.4)	26 (18.4)	29 (21.6)	46 (28.8)	33 (42.0)
>350%	77 (43.3)	105 (61.1)	106 (75.2)	60 (44.8)	75 (46.9)	153 (54.5)
Education						
≤Grade 12	61 (32.8)	30 (16.5)	7 (4.8)	55 (36.7)	36 (22.1)	7 (3.5)
Grade 13 - 16	91 (48.9)	97 (53.2)	56 (38.6)	72 (48.0)	88 (54.0)	84 (42.0)
≥ Grade 17	34 (18.3)	55 (30.2)	82 (56.2)	23 (15.3)	39 (23.9)	109 (54.5)
Pre-pregnancy BMI, mean ± SD	27.5 ±7.9	25.3 ± 5.8	22.8 ± 4.1	27.6 ± 8.0	26.7 ± 6.8	22.7 ± 3.5
Pre-pregnancy BMI Category (kg/m^2)						
Underweight	6 (3.2)	14 (7.7)	6 (4.1)	10 (6.7)	6 (3.7)	10 (5.0)
Normal weight	82 (44.1)	92 (50.6)	115 (79.3)	60 (40.0)	76 (46.6)	153 (76.5)
Overweight	48 (25.8)	41 (22.5)	15 (10.3)	35 (23.3)	40 (24.5)	29 (14.5)
Obese	50 (26.9)	35 (19.2)	9 (6.2)	45 (30.0)	41 (25.2)	8 (4.0)

Variable[c]	DASH[a]			Latent Dietary Class[b]		
	Tertile 1 (n= 186)	Tertile 2 (n=182)	Tertile 3 (n=145)	Class 1 (n=150)	Class 2 (n=163)	Class 3 (n=200)
	N (%)	N (%)	N (%)	N (%)	N (%)	N (%)
Parity						
Nulliparous	80 (43.0)	83 (45.6)	98 (67.6)	63 (42.0)	72 (44.2)	126 (63.0)
Parous	106 (57.0)	99 (54.4)	47 (32.4)	87 (58.0)	91 (55.8)	74 (37.0)
Smoking status during pregnancy						
No	141 (80.1)	161 (91.5)	137 (97.2)	113 (80.7)	132 (84.6)	194 (98.5)
Yes	35 (19.9)	15 (8.5)	4 (2.8)	27 (19.3)	24 (15.4)	3 (1.5)

[a] DASH score ranges: Tertile 1 (12-22); Tertile 2 (23-27); Tertile 3 (28-37)

[b] Class 1: high consumption of hamburgers, hot dogs, French fries, fried chicken, white bread, bacon, and soft drinks. Class 2: high consumption of vegetables, refined grains, mixed dishes, red and processed meat, poultry, salty snacks, sweets, some fast foods, and fruit juice. Class 3: high consumption of fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water

[c] All tests of differences in maternal characteristics by DASH tertile and Latent Classes were statistically significant based on χ^2 tests (p<0.001)

Table 2

Distribution of maternal dietary factors and cardiometabolic markers (mean ± SD) by DASH score tertile or latent dietary class, Pregnancy, Infection, and Nutrition (PIN) study, (n=513)

Variable[c]	DASH[a]			Latent Dietary Class[b]		
	Tertile 1 (n= 186)	Tertile 2 (n=182)	Tertile 3 (n=145)	Class 1 (n=150)	Class 2 (n=163)	Class 3 (n=200)
Dietary factors						
DASH score	18.7 ± 2.7	24.9 ± 1.4	30.2 ± 1.9	21.1 ± 4.4	22.3 ± 4.2	28.0 ± 3.6
Fruits (svg/d)	4.0 ± 3.3	4.5 ± 2.6	4.9 ± 2.6	3.7 ± 3.0	5.3 ± 3.3	4.2 ± 2.3
Vegetables (svg/d)	1.3 ± 1.2	2.3 ± 1.6	3.2 ± 2.2	1.4 ± 1.4	2.3 ± 1.7	2.6 ± 2.0
Nuts and legumes (svg/d)	0.2 ± 0.3	0.3 ± 0.3	0.4 ± 0.3	0.2 ± 0.2	0.4 ± 0.3	0.3 ± 0.3
Whole grains (svg /d)	0.4 ± 0.6	1.1 ± 1.5	1.5 ± 1.0	0.7 ± 1.7	0.9 ± 0.9	1.3 ± 0.9
Low fat dairy (svg /d)	1.2 ± 1.7	2.4 ± 2.1	3.7 ± 2.3	1.5 ± 2.0	1.9 ± 2.2	3.4 ± 2.2
Red meat (svg /d)	0.6 ± 0.7	0.4 ± 0.3	0.2 ± 0.2	0.5 ± 0.8	0.6 ± 0.3	0.2 ± 0.2
Sweetened beverages (svg /d)	3.8 ± 3.1	2.1 ± 2.2	0.9 ± 1.2	3.3 ± 3.6	3.2 ± 2.3	1.1 ± 1.2
Sodium (mg/d)	2925 ± 1193	2807 ± 1246	2626 ± 899	2217 ± 1052	3518 ± 1222	2573 ± 814
Energy intake (kcal/d)	2287 ± 964	2126 ± 859	1999 ± 623	1878 ± 914	2692 ± 869	1907 ± 504
Saturated fat	29.9 ± 14.0	26.3 ± 12.0	22.7 ± 8.5	23.9 ± 13.4	34.2 ± 12.3	22.4 ± 7.7
% energy from carbohydrates	54.3 ± 7.2	54.2 ± 7.5	56.2 ± 6.7	55.4 ± 8.5	53.9 ± 6.1	55.1 ± 6.9
% energy from protein	13.1 ± 2.3	14.6 ± 2.5	15.4 ± 2.4	13.4 ± 2.7	13.7 ± 2.0	15.4 ± 2.5
% energy from fat	34.1 ± 5.7	33.5 ± 6.1	31.6 ± 5.6	33.1 ± 6.9	34.3 ± 4.9	32.4 ± 5.6
Cardiometabolic markers						
Glucose (mg/dL)	79.1 ± 7.7	78.5 ± 7.4	78.4 ± 7.4	79.5 ± 8.4	78.8 ± 7.7	78.0 ± 6.6
Insulin (mg/dL)[d]	17.1 ± 1.7	15.4 ± 1.6	12.9 ± 1.6	17.4 ± 1.7	16.8 ± 1.6	12.7 ± 1.6
HOMA-IR[d]	3.3 ± 1.8	3.0 ± 1.7	2.5 ± 1.7	3.4 ± 1.8	3.3 ± 1.7	2.4 ± 1.6
Total Cholesterol (mg/dL)	241.3 ± 46.6	244.1 ± 43.5	250.8 ± 49.8	237.5 ± 46.3	239.7 ± 46.5	254.9 ± 45.2
Triglycerides (mg/dL)[d]	159.3 ± 1.5	158.6 ± 1.5	151.9 ± 1.4	153.1 ± 1.5	159.7 ± 1.5	157.7 ± 1.5

[a] DASH score ranges: Tertile 1 (12-22); Tertile 2 (23-27); Tertile 3 (28-37)

[b] Class 1: high consumption of hamburgers, hot dogs, French fries, fried chicken, white bread, bacon, and soft drinks. Class 2: high consumption of vegetables, refined grains, mixed dishes, red and processed meat, poultry, salty snacks, sweets, some fast foods, and fruit juice. Class 3: high consumption of fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water

[c]With the exception of sodium, glucose, total cholesterol and triglycerides in the DASH analysis, and energy from carbohydrates (%), glucose and triglycerides in the latent dietary class analysis, all other comparisons were statistically different ($P < 0.05$).

[d]Values represent geometric means of log-transformed outcomes

Table 3

Linear regression analysis for fasting cardiometabolic markers according to DASH score tertile or latent dietary class, Pregnancy, Infection, and Nutrition (PIN) Study, (n=513)

	Model 1[a]	Model 2[b]	Model 3[c]
	β (95% CI)	β (95% CI)	β (95% CI)
Glucose (mg/dL)			
DASH score			
Tertile 1	--	--	--
Tertile 2	−0.56 (−2.10, 0.97)	−0.77 (−2.37, 0.83)	−0.23 (−1.75, 1.28)
Tertile 3	−0.72 (−2.36, 0.91)	−1.01 (−2.82, 0.81)	0.29 (−1.46, 2.04)
Latent Dietary Class[d]			
Class 1	--	--	--
Class 2	−0.77 (−2.43, 0.90)	−1.01 (−2.86, 0.84)	−0.63 (−2.39, 1.12)
Class 3	−1.57 (−3.16, 0.02)	−2.33 (−4.17, −0.50)	−0.86 (−2.64, 0.92)
Insulin[c]			
DASH score			
Tertile 1	--	--	--
Tertile 2	−0.11 (−0.21, −0.00)	−0.06 (−0.16, 0.05)	−0.01 (−0.10, 0.08)
Tertile 3	−0.29 (−0.39, −0.18)	−0.18 (−0.30, −0.06)	−0.07 (−0.18, 0.04)
Latent Dietary Class			
Class 1	--	--	--
Class 2	−0.03 (−0.14, 0.08)	−0.05 (−0.17, 0.07)	−0.02 (−0.13, 0.09)
Class 3	−0.31 (−0.42, −0.21)	−0.25 (−0.37, −0.13)	−0.12 (−0.23, −0.01)
HOMA-IR[e]			
DASH score			
Tertile 1	--	--	--
Tertile 2	−0.11 (−0.23, 0.00)	−0.07 (−0.18, 0.05)	−0.01 (−0.12, 0.09)
Tertile 3	−0.29 (−0.41, −0.17)	−0.20 (−0.33, −0.06)	−0.06 (−0.18, 0.06)
Latent Dietary Class			
Class 1	--	--	--
Class 2	−0.04 (−0.16, 0.08)	−0.06 (−0.20, 0.07)	−0.02 (−0.14, 0.10)
Class 3	−0.33 (−0.45, −0.22)	−0.28 (−0.41, −0.14)	−0.13 (−0.25, −0.00)
Triglycerides[e]			
DASH score			
Tertile 1	--	--	--
Tertile 2	−0.01 (−0.08, 0.07)	−0.05 (−0.13, 0.02)	−0.04 (−0.12, 0.03)
Tertile 3	−0.05 (−0.13, 0.03)	−0.13 (−0.22, −0.42)	−0.11 (−0.19, −0.02)
Latent Dietary Class			
Class 1	--	--	--
Class 2	0.04 (−0.04, 0.13)	0.04 (−0.05, 0.13)	0.05 (−0.04, 0.14)
Class 3	0.03 (−0.05, 0.11)	−0.04 (−0.13, 0.05)	−0.01 (−0.10, 0.08)

	Model 1[a]	**Model 2**[b]	**Model 3**[c]
	β (95% CI)	**β (95% CI)**	**β (95% CI)**
Cholesterol (mg/dL)			
DASH score			
Tertile 1	---	---	---
Tertile 2	2.73 (−6.79, 12.25)	−4.50 (−14.07, 5.07)	−5.93 (−15.45, 3.59)
Tertile 3	9.48 (−0.63, 19.60)	0.57 (−10.34, 11.49)	−2.93 (−13.95, 8.08)
Latent Dietary Class			
Class 1	---	---	---
Class 2	2.22 (−7.99, 12.44)	−0.05 (−11.15, 11.16)	−0.98 (−12.03, 10.07)
Class 3	17.36 (7.60, 27.11)	9.25 (−1.77, 20.27)	5.58 (−5.63, 16.79)

DASH: Dietary Approaches to Stop Hypertension, LCA: latent class analysis; HOMA-IR: homeostasis model of assessment for insulin resistance

[a] Model 1 represents crude association.

[b] Model 2: maternal age, race, poverty level, smoking status, physical activity, parity, and energy intake.

[c] Model 3: Model 2 plus pre-pregnancy BMI.

[d] Class 1: high consumption of hamburgers, hot dogs, French fries, fried chicken, white bread, bacon, and soft drinks. Class 2: high consumption of vegetables, refined grains, mixed dishes, red and processed meat, poultry, salty snacks, sweets, some fast foods, and fruit juice. Class 3: high consumption of fruits, vegetables, whole grains, low fat dairy, breakfast bars, and water

[e] Natural log transformed