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Diet Patterns Are Associated with Circulating Metabolites and Lipid Profiles of South Asians in the United States

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ABSTRACT

Background: South Asians are at higher risk for cardiometabolic disease than many other racial/ethnic minority groups. Diet patterns in US South Asians have unique components associated with cardiometabolic disease.

Objectives: We aimed to characterize the metabolites associated with 3 representative diet patterns.

Methods: We included 722 participants in the Mediators of Atherosclerosis in South Asians Living in America (MASALA) cohort study aged 40–84 y without known cardiovascular disease. Fasting serum specimens and diet and demographic questionnaires were collected at baseline and diet patterns previously generated through principal components analysis. LC-MS–based untargeted metabolomic and lipidomic analysis was conducted with targeted integration of known metabolite and lipid signals. Linear regression models of diet pattern factor score and log-transformed metabolites adjusted for age, sex, caloric intake, and BMI and adjusted for multiple comparisons were performed, followed by elastic net linear regression of significant metabolites.

Results: There were 443 metabolites of known identity extracted from the profiling data. The "animal protein" diet pattern was associated with 61 metabolites and lipids, including glycerophospholipids phosphatidylethanolamine PE(O-16:1/20:4) and/or PE(P-16:0/20:4) (β: 0.13; 95% CI: 0.11, 0.14) and N-acyl phosphatidylethanolamines (NAPEs) NAPE(O-18:1/20:4/18:0) and/or NAPE(P-18:0/20:4/18:0) (β: 0.13; 95% CI: 0.11, 0.14), lysophosphatidylinositol (LPI) (22:6/0:0) (β: 0.14; 95% CI: 0.12, 0.17), and fatty acid (FA) (22:6) (β: 0.15; 95% CI: 0.13, 0.17). The "fried snacks, sweets, high-fat dairy" pattern was associated with 12 lipids, including PC(16:0/22:6) (β: –0.08; 95% CI: –0.09, –0.06) and FA (22:6) (β: 0.14; 95% CI: –0.17, –0.10). The "fruits, vegetables, nuts, and legumes" pattern was associated with 5 metabolites including proline betaine (β: 0.17; 95% CI: 0.09, 0.25) ($P < 0.0002$).

Conclusions: Three predominant dietary patterns in US South Asians are associated with circulating metabolites differentiated by lipids including glycerophospholipids and PUFAs and the amino acid proline betaine. *J Nutr* 2022;152:2358–2366.

Keywords: diet patterns, South Asian, cardiovascular risk, metabolomics, lipids

Introduction

South Asians (individuals of Indian, Pakistani, Bangladeshi, Nepali, and Sri Lankan descent) are at higher risk for cardiovascular disease and diabetes than many other racial and ethnic groups (1–3). About 23% of South Asians have diabetes, which often precedes coronary artery disease (4). On average, South Asians develop coronary heart disease 10 y earlier than people identifying as a different race or ethnic group, and 50% of heart attacks in South Asians occur before the age of 50 (5).

In this population, diet quality and pattern of intake are strong, modifiable risk factors for cardiometabolic disease (6, 7). Prior investigations with South Asian populations in the diaspora have characterized unique diet patterns influenced by both heritage and emigration (8, 9). We previously examined diet patterns in the Mediators of Atherosclerosis in South Asians Living in America (MASALA) cohort, in which habitual dietary intake was characterized with a culturally concordant food-frequency questionnaire (10). We identified 3 major diet patterns: Animal Protein; Fried Snacks, Sweets, High-Fat Dairy, and Fruits, Vegetables, Nuts, Legumes (11), which have unique associations with traditional risk factors for cardiometabolic disease. The increased risk associated with certain diet patterns may be tied to intermediate metabolic markers seen in South Asians, such as a pattern of atherogenic dyslipidemia, tendency

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towards larger ectopic adipose tissue deposits, and lower muscle mass and poor beta-cell function (2, 12). Little is known about the mechanisms and process by which these particular diet profiles translate into metabolic phenotypes that cause higher cardiometabolic risk.

The identification of metabolites, easily measurable and present in serum, urine, or tissue, can help to shed light on the phenotypic links between diet and cardiometabolic disease in this high-risk population (13). A panel of metabolites may both be able to serve as a biomarker for diet intake and help clarify and measure the metabolic effects of that diet intake.

In this analysis, we aimed to establish representative metabolites for predominant diet patterns in South Asians who are part of the full MASALA study.

Methods

Participants

Data were from South Asians who participated in the MASALA community-based cohort study and had complete diet and metabolomic data. The detailed methods have been described elsewhere (10). Briefly, MASALA is a prospective cohort study that enrolled community-dwelling individuals living in the San Francisco Bay Area and the greater Chicago areas from 2010 to 2013. Participants self-identified as having South Asian ancestry and were aged 40–84 y and without known cardiovascular disease. Those taking nitroglycerin, with active cancer, with impaired cognitive ability, with a life expectancy less than 5 y, who lived in a nursing home, or who had plans to relocate were excluded. The University of California, San Francisco, and Northwestern University Institutional Review Board approved the study protocol and all study participants provided written informed consent.

Demographic and diet data

Each participant underwent in-person interviews to determine age, sex, medical history, physical activity, smoking status, and alcohol intake. Food-group intake was collected with the Study of Health Assessment and Risk in Ethnic Groups (SHARE) South Asian Food Frequency Questionnaire, which was developed and validated in South Asians in Canada (14). The food-frequency questionnaire included 163 items, with 61 items unique to the South Asian diet, and assessed usual eating habits, frequency. and serving sizes over the prior 12 mo.

Dietary pattern creation

Individual food items from the SHARE food-frequency questionnaire were divided into 29 predefined subgroups reflecting likeness, underlying nutrient composition, and South Asian culinary usage. Several foods (e.g., coffee) were kept as individual categories given their high reported intake. We excluded 1 individual with incomplete food-frequency questionnaire data and another 6 who did not meet a priori criteria of daily caloric ranges (600–6000 kcal/24 h).

Principal components analysis with varimax rotation was previously used to identify the most prevalent groupings of major food-group categories in our population (15). After identifying 3 patterns that explained the majority of variance, the patterns were named according to their major components: "Animal protein" (9.3% variance); "Fried Snacks, Sweets, High-Fat Dairy" (7.4% variance); and "Fruits, Vegetables, Nuts, Legumes" (6.5% variance). Each participant was assigned a factor score for each dietary pattern based on the correlation of his or her food-frequency questionnaire data with the food groupings in the 3 prevalent patterns. The diet patterns Animal Protein and Fried Snacks, Sweets, High-Fat Dairy each had continuous factor scores that were divided into tertiles for ease of interpretation.

Metabolic Profiling by Ultra-Performance LC-MS

A total of 754 serum samples obtained at the baseline examination (2010–2013) were analyzed by ultra-performance LC-MS (UPLC-MS) using previously described analytical and quality-control procedures (16, 17). Sample analysis was performed in an order designed to be orthogonal to clinical and demographic data metadata. For quality-control assessment and data pre-processing, a study reference (SR) sample was prepared by pooling equal parts of each study sample.

Serum samples were prepared and analyzed using UPLC-MS, as previously published (16, 17). In brief, 50-μL aliquots were taken from each sample, diluted 1:1 with ultrapure water for lipid profiling and 1:1.4 for small molecule profiling. Protein was removed by addition of organic solvent to the diluted sample (4 volumes of isopropanol per volume of diluted sample for lipidomic profiling and 3 volumes of acetonitrile per volume of diluted sample for small molecule profiling) followed by mixing and centrifugation to yield a homogenous supernatant. Aliquot sets of prepared samples were subjected to chromatographic separation using an Acquity UPLC (Waters Corporation) system. Lipidomic profiling was performed using reverse-phase chromatography (RPC) with a 2.1- × 100-mm Acquity BEH C8 column maintained at 55°C. The chromatographic separation was performed using a binary mobile phase system consisting of (A) a 50:25:25 mixture of H_2O:Acetonitrile (ACN):Isopropanol (IPA) with 5 mm ammonium acetate, 0.05% acetic acid, and 20 μM phosphoric acid and (B) 50:50 ACN:IPA with 5 mm ammonium acetate and 0.05% acetic acid. Polar metabolite profiling was performed using hydrophilic interaction LC (HILIC) with a 2.1- × 150-mm Acquity BEH HILIC column maintained at 40°C. The chromatographic separation was performed using a binary mobile phase system consisting of (A) acetonitrile with 0.1% formic acid and (B) 20 mM ammonium formate in water with 0.1% formic acid. Both separation types were coupled to high-resolution MS (Xevo G2-S TOF mass spectrometers; Waters Corporation) via a Z-spray electrospray ionization source. The lipidomic profiling assay was conducted in both positive and negative ion modes (generating lipid RPC+ and lipid RPC– datasets), while the HILIC assay was performed in the positive ion mode only (generating the HILIC+ dataset). An SR sample was acquired every 10 study samples throughout the analysis. In addition, a dilution series was created from the SR and analyzed immediately prior to and after the study sample analysis for use in signal filtering, as described previously (16).

Raw data were converted to the mzML open-source format and signals below an absolute intensity threshold of 100 counts were removed using the MSConvert tool in ProteoWizard (18). Metabolite signal extraction was performed using PeakPantheR, an open-source

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Supplemental Tables 1–4 are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/jn/.
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Abbreviations used: ACN, Acetonitrile; CAR, acylcarnitine; CER(d), Ceramide; FA, Fatty Acid; HILIC, hydrophilic interaction liquid chromatography; IPA, Isopropanol; LPC, Lysophosphatidylcholine; LPE, Lysophosphatidylethanolamine; LPI, Lysophosphatidylinositol; MASALA, Mediators of Atherosclerosis in South Asians Living in America; MET, metabolic equivalent; NAFLD, nonalcoholic fatty liver disease; NAPE, N-acyl phosphatidylethanolamine; PC, phosphatidylcholine; PE, phosphatidylethanolamine; RPC, reverse-phase chromatography; SHARE, Study of Health Assessment and Risk in Ethnic Groups; SM, sphingomyelin; SR, study reference; UPLC-MS, ultra-performance liquid chromatography–mass spectrometry.

package to detect, integrate, and report predefined and annotated lipids and metabolites from an in-house database (19). Elimination of potential run-order effects and filtering of the extracted metabolites were performed using the nPYc-Toolbox, an open-source package for data pre-processing (20). Only those measured with high accuracy (relative CV in SR samples <20%) and high precision (correlation to dilution in SR dilution series >0.8) were retained and put forward for biological analysis. Of the 754 total study samples, 32 were not included in our analysis due to insufficient sample volume and 5 were excluded due to missed injection in the HILIC assay.

Cardiometabolic factors measured at baseline

Weight was determined using a digital scale, height with a stadiometer, and waist circumference using a measuring tape halfway between the lower ribs and the anterior superior iliac spine, at the site of greatest circumference. Blood samples were obtained after a requested 12-h fast. Fasting plasma glucose was measured using the hexokinase method (Quest Diagnostics). An oral-glucose-tolerance test was performed, in which participants consumed a 75-g oral-glucose solution, and blood samples for plasma glucose and insulin were taken after 120 min. Type 2 diabetes was defined as fasting glucose ≥126 mg/dL, 2-h post-challenge glucose ≥200 mg/dL, or use of a glucose-lowering medication. A total of 717 participants were included in our analysis.

Statistical methods

Before modeling, relative abundances of metabolites were log-transformed to reduce the potential for outliers to influence the model. Multivariable linear regression analyses were used to determine associations of diet pattern factor score and relative abundance of each independent metabolite. The analyses were adjusted for age, sex, calories per day, and BMI in model 1 and further adjusted for presence of diabetes, hypertension, use of statin medication, smoking, and alcohol intake of ≥1 drink/wk as categorical variables and exercise [metabolic equivalent (MET)-min/wk] as a continuous variable. We applied the conservative Bonferroni method to adjust for multiple comparisons, with an alpha <0.00002 deemed significant. To adjust for unreliable parameter estimates that may occur when using multiple regression models in the setting of multicollinearity, we performed an elastic-net regularized regression model to evaluate metabolites that were significant in independent analyses. The elastic-net model allowed for a penalized logistic regression on all biomarkers simultaneously to identify the metabolites most highly associated with diet pattern score. Optimal parameters for the penalty value (α) and the regularization penalty (λ) were determined by 10-fold cross-validation. Briefly, data in the full dataset were randomly assigned to 1 of 2 equal-sized datasets. Model performance was judged based on root mean square error, with the model chosen minimizing mean cross-validated error. Optimization was completed using STATA's "elasticnet" and post-estimation commands for model prediction (StataCorp). We then further adjusted these linear regression models for physical activity, diabetes, and family history of diabetes. The analysis was completed using STATA (version 16.1, 2021; StataCorp).

Results

In total, 443 metabolites and lipids were examined in this analysis (**Supplemental Table 1**). MASALA participants in the highest tertile of factor score of the Animal Protein pattern were less likely to be women, had a lower total daily energy intake, but were of a similar BMI than those who most often consumed the Fried Snacks, Sweets, High-Fat Dairy, or Fruits, Vegetables, Nuts, Legumes patterns (**Table 1**). A similar proportion of women most often consumed the Fried Snacks, Sweets, High-Fat Dairy Pattern and Fruits, Vegetables, Nuts, Legumes diet patterns (47%).

After elastic-net regularized regression, and further adjustment for relevant covariates, the Animal Protein diet pattern was associated with 61 metabolite and lipid species. It was positively associated with phospholipids, sphingomyelins, ceramides, and other lipid species including omega-3 (n–3) fatty acids, and negatively associated with long-chain acylcarnitines and trigonelline. The metabolites most highly associated with the Animal Protein diet pattern were as follows: phosphotidylethanolamine (PE)(O-16:1/20:4) and/or PE(P-16:0/20:4) (0.13; 95% CI: 0.11, 0.14) and N-acyl phosphatidylethanolamines (NAPEs) (O-18:1/20:4/18:0) and/or NAPE(P-18:0/20:4/18) (0.13; 95% CI: 0.11, 0.14), LPI (22:6/0:0) (0.14; 95% CI: 0.12, 0.17) and fatty acids (FAs) (22:6) (0.15; 95% CI: 0.13, 0.17) (**Table 2**). The Fried Snacks, Sweets, High-Fat Dairy pattern was associated with 12 lipids, the top 2 associations of which were phosphatidylcholine (PC)(16:0/22:6) (–0.08; 95% CI: –0.09, –0.06) and FA(22:6) (0.14; 95% CI: –0.17, –0.10) (**Table 3**). The Fruits, Vegetables, Nuts, Legumes diet was associated with 5 metabolites, including a positive association with proline betaine (0.17; 95% CI: 0.09, 0.25) (**Table 4**).

Discussion

Participants in the MASALA study consumed 3 predominant dietary patterns: Animal Protein; Fried Snacks, Sweets, High-Fat Dairy; and Fruits, Vegetables, Nuts, Legumes, which were each associated with particular metabolite and lipid patterns. The metabolic profile associated with Animal Protein pattern was represented by glycerophospholipids, acylcarnitines, and ceramides, which carry high metabolic risk. The Fried Snacks, Sweets, High-Fat Dairy Pattern was inversely associated with a number of lipids, including an n–3 fatty acid derived from seafood and linked to lower cardiovascular risk (21). Higher consumption of the Fruits, Vegetables, Nuts, Legumes pattern was associated with a higher abundance of proline betaine, a marker of citrus consumption, and a lower risk for type 2 diabetes in prior studies (22) and lower relative abundance of several lipid subspecies.

The metabolite and lipid patterns associated with a high consumption of each diet pattern have implications for metabolic health. In particular, proline betaine was positively associated with the most "prudent" diet pattern, Fruits, Vegetables, Nuts, Legumes, and negatively associated with the Animal Protein diet pattern. There is a correlation between proline betaine and fruit intake in this sample (**Supplemental Table 2**). This amino acid and its analog glycine betaine have been associated with lower risk for diabetes in the Diabetes Prevention Program and other trials and cohort studies (22, 23). Betaine is derived from the amino acid glycine and acts as a methyl donor to allow the conversion of homocysteine to methionine (24). Proline betaine is also a biomarker of citrus consumption (25). Deficiency of betaine is additionally linked toh increased severity of nonalcoholic fatty liver disease (NAFLD) (26). In our prior work, the Fruits, Vegetables, Nuts, Legumes pattern was associated with a lower prevalence of metabolic syndrome (11). Despite these positive observational findings and promising preclinical data from animal studies, direct supplementation of betaine in humans during a randomized controlled trial showed only minor improvements in fasting glucose, and no changes in dynamic measurements of insulin sensitivity and intrahepatic triglycerides (27). Together, this suggests that an exploration of the choline-betaine metabolic pathways and downstream metabolites may yield insights into the pathogenesis of prediabetes and NAFLD.

TABLE 1 Baseline characteristics of MASALA study participants by tertile of diet pattern[1]

	Animal Protein (alcohol, coffee, eggs, fish, pasta, pizza, poultry, red meat, refined grains)			Fried Snacks, Sweets, High-Fat Dairy (added fat, butter/ghee, fried snacks, high-fat dairy, sugar-sweetened beverages, legumes, potatoes, refined grains, rice, whole grains)			Fruits, Vegetables, Nuts Legumes (fruit, fruit juice, legumes, nuts, vegetable oil, vegetables, whole grains)		
	Tertile 1	Tertile 2	Tertile 3	Tertile 1	Tertile 2	Tertile 3	Tertile 1	Tertile 2	Tertile 3
n	245	233	225	234	238	231	229	239	235
Women, *n* (%)	141 (58)	105 (45)	70 (31)	122 (52)	112 (47)	82 (36)	97 (42)	115 (48)	104 (44)
Age, y	56 (9)	56 (9)	54 (9)	56 (10)	56 (10)	55 (9)	54 (9)	55 (9)	57 (9)
BMI, kg/m^2	26 (4)	26 (4)	26 (4)	26 (4)	26 (4)	26 (4)	26 (4)	26 (4)	26 (4)
Smoker, *n* (%)									
Never	228 (93)	192 (82)	163 (72)	198 (85)	197 (83)	188 (81)	182 (79)	202 (85)	199 (85)
Former	15 (6)	36 (15)	46 (20)	30 (13)	32 (13)	35 (15)	33 (14)	35 (15)	29 (12)
Current	2 (1)	5 (2)	16 (7)	6 (3)	9 (4)	8 (3)	14 (6)	2 (1)	7 (3)
Alcohol use, *n* (%)	33 (13)	74 (31)	133 (59)	86 (37)	78 (33)	76 (33)	82 (36)	77 (32)	81 (34)
Exercise, MET-min/wk	983 [1515]	1080 [1523]	945 [1300]	1170 [1845]	960 [1560]	735 [1542]	690 [1365]	1035 [1523]	1373 [1665]
Energy intake, kcal/d	1630 (461)	1613 (444)	1820 (555)	1366 (354)	1662 (413)	2035 (470)	1348 (342)	1664 (393)	2037 (480)
Diabetes, *n* (%)	77 (26)	75 (25)	72 (24)	64 (27)	60 (25)	50 (22)	65 (28)	60 (25)	49 (21)
Hypertension, *n* (%)	96 (39)	97 (42)	90 (40)	95 (41)	105 (44)	83 (36)	93 (41)	104 (44)	86 (37)

[1] Values are means (SDs), medians [IQR], or frequencies (%). MASALA, Mediators of Atherosclerosis in South Asians Living in America; MET, metabolic equivalent.

TABLE 2 Metabolites associated with the Animal Protein diet pattern, elastic-net regularized regression[1]

	Model 1, adjusted for age, sex, BMI, energy intake[2,3]				Model 2, fully adjusted[4]			
	ß[2]	95% CI (lower)	95% CI (upper)	*P*	ß[3]	95% CI (lower)	95% CI (upper)	*P*
Creatine	0.08	0.06	0.1	1.21×10^{-15}	0.08	0.06	0.10	1.47×10^{-14}
Carnitine	0.02	0.01	0.03	2.79×10^{-07}	0.02	0.01	0.03	9.13×10^{-07}
CAR(3:0) (propionylcarnitine)	0.03	0.02	0.05	1.89×10^{-05}	0.04	0.02	0.06	8.99×10^{-06}
Proline betaine	−0.11	−0.17	−0.06	1.41 × 10–05	−0.12	−0.17	−0.06	3.34×10^{-05}
Pipecolate/N-methyl proline	−0.07	−0.1	−0.03	1.34 × 10–04	−0.07	−0.10	−0.03	3.67 × 10–04
Taurine	0.03	0.02	0.05	3.28×10^{-05}	0.04	0.02	0.05	8.82×10^{-05}
Trigonelline	−0.16	−0.19	−0.12	1.89×10^{-17}	−0.17	−0.21	−0.13	7.93×10^{-18}
Trimethylaminoacetone	0.04	0.03	0.06	1.55×10^{-06}	0.04	0.02	0.06	5.51×10^{-05}
Methyladenosine	−0.01	−0.02	−0.01	1.79×10^{-04}	−0.01	−0.02	−0.00	1.60×10^{-03}
CAR(14:2)	−0.05	−0.07	−0.03	4.91×10^{-05}	−0.04	−0.06	−0.01	6.62×10^{-03}
CAR(18:0)	0.03	0.02	0.05	1.47×10^{-06}	0.03	0.02	0.05	4.82×10^{-05}
CAR(18:3)	−0.04	−0.06	−0.02	1.03×10^{-04}	−0.03	−0.05	−0.01	0.01
CAR(20:1)	−0.04	−0.05	−0.02	3.33×10^{-05}	-0.04	-0.05	-0.02	8.80×10^{-05}
CAR(20:2)	−0.06	−0.07	−0.04	4.72×10^{-11}	−0.05	−0.07	−0.04	4.47×10^{-09}
CAR(20:3)	−0.05	−0.07	−0.03	3.56×10^{-08}	−0.05	−0.07	−0.03	3.13×10^{-07}
CE(20:4)[5]	0.03	0.02	0.04	1.79×10^{-06}	0.03	0.01	0.04	4.42×10^{-05}
CE(20:5)	0.1	0.07	0.12	4.08×10^{-15}	0.08	0.06	0.11	3.20×10^{-10}
Cer(d18:1/26:1)	0.07	0.05	0.09	4.51×10^{-12}	0.06	0.04	0.08	1.17×10^{-08}
Cer(d20:1/24:0)	0.07	0.05	0.09	8.36×10^{-10}	0.07	0.05	0.09	3.33×10^{-08}
SulfoHexCer(d18:1/18:0)	0.05	0.03	0.06	1.25×10^{-08}	0.05	0.03	0.06	1.51×10^{-07}
SulfoHexCer(d18:1/22:0OH)	0.05	0.03	0.07	2.48×10^{-09}	0.05	0.03	0.07	2.19×10^{-08}
SulfoHexCer(d18:1/24:0OH)	0.03	0.01	0.05	1.40×10^{-04}	0.03	0.01	0.05	3.57×10^{-04}
Cer(d18:2/18:0)	0.05	0.03	0.07	3.62×10^{-07}	0.04	0.02	0.06	6.61×10^{-05}
LPC(17:1/0:0)	0.03	0.01	0.04	6.36×10^{-05}	0.03	0.01	0.04	5.00×10^{-04}
LPC(20:0/0:0)	−0.04	−0.06	−0.02	1.23×10^{-06}	−0.03	−0.05	−0.02	1.19×10^{-04}
LPC(20:1/0:0)	−0.04	−0.06	−0.03	1.35×10^{-06}	0.04	−0.06	0.02	3.63×10^{-05}
LPC(22:6/0:0)	0.1	0.08	0.12	4.78×10^{-26}	0.09	0.07	0.11	5.76×10^{-19}
LPE(18:1/0:0)	−0.04	−0.06	−0.02	1.73×10^{-06}	−0.04	−0.06	−0.02	4.43×10^{-06}
LPE(18:2/0:0)	−0.05	−0.07	−0.04	1.23×10^{-10}	−0.05	−0.06	0.03	3.76×10^{-08}
PE(16:0/20:3) and PE(18:1/18:2) and PE(18:0/18:3)	−0.07	−0.09	−0.05	2.57×10^{-12}	0.07	−0.09	−0.05	6.63×10^{-10}
PC(16:0/18:3)	−0.05	−0.07	−0.03	2.92×10^{-06}	0.05	−0.07	−0.03	6.42×10^{-06}
PC(16:0/20:4)	0.02	0.01	0.04	1.21×10^{-05}	0.02	0.01	0.03	3.21×10^{-03}
PC(16:0/22:4)	−0.03	−0.05	−0.02	1.15×10^{-04}	−0.03	−0.05	−0.01	3.55×10^{-04}
PC(18:1/20:3)	−0.06	−0.07	−0.04	9.17×10^{-14}	−0.05	−0.07	−0.04	1.20×10^{-11}
PC(34:0), PC(18:0/16:0), and PC(16:0/18:0)	0.02	0.01	0.04	5.01×10^{-05}	0.02	0.01	0.03	1.92×10^{-04}
PE(16:0/18:1)	−0.05	−0.07	−0.03	2.13×10^{-04}	−0.06	−0.08	−0.04	1.51×10^{-06}
PE(18:1/18:2)	−0.07	−0.09	−0.05	1.21×10^{-10}	−0.07	−0.09	−0.04	8.29×10^{-09}
PE(20:1/20:4)	−0.07	−0.09	−0.05	1.29×10^{-04}	−0.08	−0.10	−0.06	3.90×10^{-11}

(*Continued*)

TABLE 2 (*Continued*)

	Model 1, adjusted for age, sex, BMI, energy intake[2,3]				Model 2, fully adjusted[4]			
	ß[2]	95% CI (lower)	95% CI (upper)	*P*	ß[3]	95% CI (lower)	95% CI (upper)	*P*
LPC(P-18:0/0:0)	0.07	0.06	0.09	5.58×10^{-21}	0.07	0.05	0.09	3.85×10^{-17}
PC(O-16:0/18:2)	0.07	0.06	0.09	8.72×10^{-21}	0.08	0.06	0.09	1.96×10^{-24}
PE(18:0/16:0)	−0.05	−0.07	−0.03	1.15×10^{-08}	−0.06	−0.07	0.04	4.25×10^{-09}
SM(d18:1/18:0)	0.03	0.02	0.04	5.00×10^{-09}	0.03	0.02	0.04	2.72×10^{-07}
SM(d35:1)	0.03	0.02	0.04	3.96×10^{-06}	0.03	0.02	0.05	6.53×10^{-07}
TG(52:4)	−0.03	−0.05	−0.02	1.72×10^{-04}	−0.02	−0.04	−0.01	0.01
FA(18:4)	0.05	0.03	0.08	3.28×10^{-05}	0.05	0.03	0.08	1.50×10^{-04}
FA(20:4)	0.03	0.01	0.04	1.47×10^{-04}	0.03	0.01	0.04	2.77×10^{-04}
FA(22:5confi)	0.09	0.06	0.11	2.36×10^{-13}	0.08	0.05	0.10	3.68×10^{-10}
FA(22:6)	0.15	0.13	0.17	1.41×10^{-32}	0.14	0.11	0.16	8.90×10^{-25}
FA(24:5)	0.07	0.05	0.1	3.86×10^{-07}	0.07	0.04	0.10	8.25×10^{-06}
LPI(16:1/0:0)	0.1	0.07	0.13	1.07×10^{-09}	0.09	0.06	0.13	1.19×10^{-07}
LPI(20:4/0:0)	0.04	0.03	0.06	9.51×10^{-08}	0.04	0.02	0.05	1.98×10^{-06}
LPI(22:6/0:0)	0.14	0.12	0.17	1.14×10^{-31}	0.14	0.11	0.16	6.41×10^{-25}
PE(O-16:1/20:4) and/or PE(P-16:0/20:4)	0.13	0.11	0.14	3.35×10^{-63}	0.13	0.11	0.14	2.44×10^{-56}
PA(O-18:1/20:4) and/or PA(P-18:0/20:4)	0.13	0.11	0.15	3.11×10^{-36}	0.13	0.11	0.15	2.32×10^{-30}
NAPE(O-18:1/18:1/16:0) and/or NAPE(P-18:0/18:1/16:0)	0.03	0.02	0.05	4.60×10^{-07}	0.03	0.02	0.05	1.48×10^{-05}
PE(O-18:2/20:4) and/or PE(P-18:1/20:4)	0.1	0.09	0.11	8.18×10^{-40}	0.1	0.09	0.12	6.93×10^{-36}
PE(O-16:0/22:6)	0.11	0.09	0.12	8.78×10^{-41}	0.11	0.09	0.12	1.23×10^{-35}
PE(O-18:1/18:2) and/or PE(P-18:0/18:2)	0.04	0.03	0.06	6.30×10^{-09}	0.05	0.03	0.06	1.51×10^{-09}
NAPE(O-18:1/20:4/16:0) and/or NAPE(P-18:0/20:4/16:0)	0.1	0.09	0.11	6.58×10^{-43}	0.1	0.08	0.11	$3.95 \times 10–35$
PE(O-18:1/18:1) and/or PE(P-(18:0/18:1)	0.09	0.07	0.1	9.05×10^{-25}	−0.05	−0.07	−0.04	1.20×10^{-11}
NAPE(O-18:1/20:4/18:0) and/or NAPE(P-18:0/20:4/18:0)	0.13	0.11	0.14	4.63×10^{-47}	0.12	0.11	0.14	9.35×10^{-39}

[1] All metabolites are significant at $P < 0.0002$. CAR, acylcarnitine; CE, Cholesterol Ester; CER(d), Ceramide; FA, Fatty Acid; LPC, Lysophosphatidylcholine; LPE, Lysophosphatidylethanolamine; LPI, Lysophosphatidylinositol; MET, metabolic equivalent; NAPE, N-acyl phosphatidylethanolamine; PC, phosphatidylcholine; PE, phosphatidylethanolamine; SM, sphingomyelin; SulfoHexosyl Ceramide, SulfoHexCer(d).
[2] Adjusted for age, sex, BMI, and energy intake.
[3] Increase in log-metabolites per 1-point increase in dietary pattern scores.
[4] Further adjusted for diabetes, normoglycemic prediabetes or diabetes, hypertension, statin use, physical activity (MET-min/wk), alcohol use ≥1 drink/wk, and smoking.

TABLE 3 Metabolites associated with Fried Snacks, Sweets, High-Fat Dairy diet pattern elastic net regularized regression adjusted for age, sex, BMI, and energy intake[1]

	Model 1, adjusted for age, sex, BMI, energy intake[2,3]				Model 2, fully adjusted[4]			
	ß[2]	95% CI (lower)	95% CI (upper)	*P*	ß[3]	95% CI (lower)	95% CI (upper)	*P*
PC(16:0/22:6)	−0.09	−0.11	−0.06	1.16×10^{-08}	−0.07	−0.10	−0.04	1.30×10^{-05}
LPE(18:2/0:0)	0.05	0.02	0.07	4.37×10^{-05}	0.03	0.01	0.06	4.13×10^{-03}
LPI(22:6/0:0)	−0.08	−0.12	−0.04	1.00×10^{-05}	−0.07	−0.11	−0.03	3.08×10^{-04}
PC(16:0/22:4)	0.07	0.04	0.09	1.73×10^{-08}	0.05	0.03	0.08	1.48×10^{-05}
PC(18:0/22:4)	0.08	0.05	0.11	1.71×10^{-07}	0.07	0.04	0.10	6.49×10^{-06}
PC(16:0/20:5)	−0.09	−0.13	−0.06	1.65×10^{-08}	−0.07	−0.11	−0.04	8.54×10^{-06}
PC(16:0/22:6)	−0.08	−0.09	−0.06	1.71×10^{-16}	−0.06	−0.08	−0.05	1.22×10^{-11}
PA(16:0/18:1)	−0.04	−0.06	−0.02	8.83×10^{-05}	−0.04	−0.06	−0.01	2.59×10^{-03}
FA(22:6)	−0.14	−0.17	−0.1	1.96×10^{-13}	−0.11	−0.15	−0.07	7.22×10^{-09}
PC(18:0/22:5)	0.07	0.04	0.11	1.52×10^{-05}	0.07	0.03	0.10	9.11×10^{-05}
SulfoHexCerd(18:1/24:0-OH)	−0.05	−0.07	−0.02	6.15×10^{-05}	−0.05	−0.07	−0.02	5.74×10^{-05}
SulfoHexCerd(18:1/24:1-OH)	−0.05	−0.07	−0.03	3.55×10^{-05}	−0.04	−0.07	−0.02	2.72×10^{-04}

[1]All metabolites are significant at $P < 0.0002$. FA, Fatty Acid; LPC, Lysophosphatidylcholine; LPE, Lysophosphatidylethanolamine; LPI, Lysophosphatidylinositol; MET, metabolic equivalent; PC, phosphatidylcholine; PE, phosphatidylethanolamine; SulfoHexosyl Ceramide, SulfoHexCer(d).
[2]Adjusted for age, sex, BMI, and energy intake.
[3]Increase in log-metabolites per 1-point increase in dietary pattern scores.
[4]Further adjusted for diabetes, normoglycemic prediabetes or diabetes, hypertension, statin use, physical activity (MET-min/wk), alcohol use ≥ 1 drink/wk, and smoking.

Long- and short-chain acylcarnitines have previously been associated with prevalent and incident diabetes (28, 29). Short-chain acylcarnitines, specifically acylcarnitine (CAR)com(3:0) and CAR(5:0) acylcarnitines, are breakdown products of branched-chain amino acid metabolism and are associated with insulin resistance (30). In a previous assessment diet patterns and metabolites in the MASALA pilot study ($n = 150$), a similar "Western/non-vegetarian" diet pattern was associated with short-chain acylcarnitines (31). In our study, there was a direct association between increased consumption of the Animal Protein pattern and propionylcarnitine [CAR(3:0)]. There have been conflicting associations between long-chain acylcarnitines and the presence of diabetes. Impaired FA oxidation and oxidative stress due to peripheral insulin resistance may cause a buildup of long-chain acylcarnitines (29), resulting in a decrease in insulin synthesis and associations with prevalent diabetes. Conversely, several cohort studies, including the PREvención con DIeta MEDiterránea (PREDIMED) study and our prior work in the MASALA study, show inverse associations between long-chain acylcarnitine abundance and both prevalent diabetes and future glucose intolerance (32, 33). The current investigation found a positive association between the Animal Protein pattern and CAR(18:0) and an inverse association with CAR(14:2), CAR(18:3), CAR(20:2), and CAR(20:3). In support of the association between this diet pattern and circulating CAR(18:0), a randomized trial of red meat intake also revealed positive associations with CAR(18:0) (34). Our prior work in the MASALA cohort identified a relation between higher baseline CAR(18:0) and subsequent lower glycated hemoglobin at 5-y follow-up (33) in cohort members without baseline diabetes. These findings suggest that animal protein intake is associated with CAR(18:0); however, further associations with diabetes are varied in this population, and may depend on the prevalence of other diet components.

The Animal Protein pattern was also associated with a higher abundance of multiple ceramides and sphingomyelins, including Ceramide (Cer)(d18:1/26:1) and sphingomyelin (SM)(d18:1/18:0). Ceramides, which are bioactive sphingolipids, have strong ties with diabetes risk (35, 36). Both circulating ceramides and sphingomyelins have been associated with impaired glucose homeostasis (37, 38). Ceramides are also associated with intake of saturated fats and with NAFLD (39).

In our investigation, NAPEs were associated with consumption of the Animal Protein pattern, and were correlated with red meat, poultry, fish, eggs, and coffee intake (**Supplemental Table 3**). NAPEs' hydrolysis generates N-acylethanolamines that are precursors of endocannabinoids synthesized in phospholipid membranes. Endocannabinoids may be involved in signaling between the gut microbiotia and adipose tissue,

TABLE 4 Metabolites associated with Fruits, Vegetables, Nuts, Legumes diet pattern elastic-net regularized regression adjusted for age, sex, BMI, and energy intake[1]

	Model 1, adjusted for age, sex, BMI, energy intake[2,3]				Model 2, fully adjusted[4]			
	ß[2]	95% CI (lower)	95% CI (upper)	*P*	ß[3]	95% CI (lower)	95% CI (upper)	*P*
Proline betaine	0.17	0.09	0.25	1.0×10^{-04}	0.18	0.09	0.26	3.65×10^{-05}
LPC(22:4/0:0)	−0.08	−0.11	−0.04	5.86×10^{-06}	−0.07	−0.10	−0.03	1.17×10^{-04}
PC(18:0/22:4)	−0.06	−0.09	−0.03	1.0×10^{-04}	−0.05	−0.09	−0.20	1.67×10^{-03}
SM(d19:1/16:0)	−0.07	−0.1	−0.04	7.40×10^{-05}	−0.06	−0.09	−0.03	1.42×10^{-05}
LPE(22:4/0:0)	−0.12	−0.18	−0.07	1.36×10^{-05}	−0.11	−0.17	−0.05	1.43×10^{-04}

[1]All metabolites are significant at $P < 0.0002$. LPC, Lysophosphatidylcholine; LPE, Lysophosphatidylethanolamine; MET, metabolic equivalent; PC, phosphatidylcholine; SM, sphingomyelin.
[2]Adjusted for age, sex, BMI, and energy intake.
[3]Increase in log-metabolites per 1-point increase in dietary pattern scores.
[4]Further adjusted for diabetes, normoglycemic prediabetes or diabetes, hypertension, statin use, physical activity (MET-min/wk), alcohol use ≥1 drink/wk, and smoking.

and have been implicated in metabolic disorders such as obesity and type 2 diabetes (40). In some reports NAPEs have been shown to be increased in plasma after high-fat feeding and regulate food intake (41). Phosphotidylethanolamines PE(O-16:1/20:4) and/or PE(P-16:0/20:4) were significantly and positively associated with intake of the Animal Protein pattern, and are an essential bioactive lipid abundant in mammalian cells (42). One study has shown a potential link between this broader lipid species class and decreased odds of acute coronary syndrome (43); however, the particular risk conferred by the lipids found in our analysis is not known.

Several important PUFAs differed between patterns, including lipids with DHA FA(22:6) moieties. These n–3 fatty acids are correlated with the major non-vegetarian components, including red meat, poultry, eggs, and fish consumption in the Animal Protein pattern (Supplemental Table 3); negatively correlated with butter/ghee and legume intake in the Fried Snacks, Sweets, High-Fat Dairy diet pattern (**Supplemental Table 4**); and have previously been linked to a lower risk of cardiovascular disease (44). Lipids with these moieties are lower in abundance with greater consumption of the Fried Snacks, Sweets, High-Fat Dairy pattern, suggesting that there may be lower consumption of these potentially beneficial FAs in this unhealthful vegetarian pattern. n–6 FAs found in lean meat, milk, and eggs contain arachidonic acid FA(20:4), which is abundant in phospholipids and important for cellular signaling in the brain and skeletal muscle, and was higher with consumption of the Animal Protein pattern. High levels of this FA may be affected by oxidative stress and play a role in the pathogenesis of fatty liver and diabetes (45) and cardiovascular disease (46).

In conclusion, our findings suggest that prevalent diet patterns in the MASALA study are associated with groups of metabolites and lipids linked with cardiometabolic disease. The Fruits, Vegetables, Nuts, Legumes pattern associated with proline betaine has been linked to reduced risk for diabetes. The Animal Protein pattern was associated with NAPEs, sphingomyelins, and ceramides and long- and short-chain acylcarnitines. Furthermore, the Animal Protein and Fried Snacks, Sweets, High-Fat Dairy patterns had opposite associations with long-chain n–3 FAs, which have been linked to lower risk of cardiovascular disease. These conclusions are limited by the absence of data on intraindividual variability of metabolites. These findings support the next steps in the investigation of diet and metabolites: the study of metabolites as biomarkers for measuring diet quality and to determine targeted dietary advice to reduce risk of cardiometabolic disease.

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Data Availability

Data described in the manuscript, code book, and analytic code will be made available upon request pending request to MASALA Study Steering Committee for reasons of participant confidentiality.

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