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Associations of Air Pollution, Obesity and Cardiometabolic Health in Young Adults: The Meta-AIR Study

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Abstract

Objective—Growing evidence indicates exposure to air pollution contributes to obesity and cardiometabolic disease risk in children and adults, however studies are lacking in young adulthood, an important transitional period in the life course. The aim of this study was to examine the associations of short- and long-term regional ambient and near-roadway air pollution (NRAP) exposures on adiposity and cardiometabolic health in young adults aged 17–22 years.

Methods—From 2014–2018, a subset of participants (n=158) were recruited from the Children's Health Study to participate in the Meta-AIR (Metabolic and Asthma Incidence Research) study to assess obesity (body composition and abdominal adiposity) and cardiometabolic health (fasting glucose, fasting insulin and lipid profiles) measures. Prior 1-month and 1-year average air pollution exposures were calculated from residential addresses. This included nitrogen dioxide $(NO₂)$, ozone $(O₃)$, particulate matter with aerodynamic diameter <10 µm (PM10), particulate matter with aerodynamic diameter $\langle 2.5 \mu m (PM_2, 5) \rangle$ and NRAP (freeway, non-freeway, and total nitrogen oxides (NO_x)) exposures. Linear regression models examined associations of prior 1month (short-term) and 1-year (long-term) air pollution exposures on obesity and cardiometabolic factors adjusting for covariates and past childhood air pollution exposures.

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Authors' contributions: JSK conceived the research question, reviewed the data, performed the data analysis, and wrote the manuscript. ZC, TLA, and CTC assisted with data analysis, reviewed the results, and contributed to writing of the manuscript. FL provided air pollution exposure data and contributed to manuscript writing. KB provided guidance for the data analysis, reviewed the results, and contributed to writing of the manuscript. FDG conceived the primary study design, obtained funding for the study, reviewed the results, and contributed to writing of the manuscript. All authors have reviewed and approved the final manuscript.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Results—In the Meta-AIR study, we conducted a comprehensive analysis with short- and longterm regional ambient and NRAP exposures (in both single- and multi-pollutant models) and obesity- and cardiometabolic-related outcomes and found associations with a few outcomes. A 1 standard deviation (SD) change in long-term $NO₂$ exposure was associated with a 11.3 mg/dL higher level of total cholesterol (p=0.04) and 9.4 mg/dL higher level of low-density lipoproteins (LDL)-cholesterol ($p=0.04$). Among obese participants, associations between long-term $NO₂$ and total cholesterol and LDL-cholesterol were 4.5 and 9 times larger than the associations in nonobese participants (p_{interaction}=0.008 and 0.03, respectively). Additionally, we observed a statistically significant association with increased short-term $O₃$ exposure and higher triglyceride and very-low-density lipoprotein (VLDL) cholesterol levels (p=0.04), lower high-density lipoprotein (HDL) cholesterol levels ($p=0.03$), and higher hepatic fat levels ($p=0.02$). Amongst glucose-related factors, long-term $PM_{2.5}$ exposure was associated with higher levels of insulin area under the curve $(p=0.03)$. There were no other statistically significant associations with short- or long-term air pollutants and BMI, other measures of adiposity, and cardiometabolic outcomes.

Conclusion—Higher exposure to regional air pollutants, namely prior 1-year average NO₂, was associated with higher fasting serum lipid measures. These associations were more pronounced in obese participants, suggesting obesity may exacerbate the effects of air pollution exposure on lipid levels in young adults. This study did not find any other associations between short- and long-term ambient and NRAP exposures across a range of other obesity and cardiometabolic indicators. Further studies in young adults are warranted as our study suggests potential deleterious associations of both short- and long-term air pollution exposures and lipid metabolism.

Keywords

ambient air pollution; near-roadway air pollution; obesity; cardiometabolic health; young adult

1. Introduction

New data shows significant increasing obesity trends in both youth and adults from 1999– 2016 (1). Early onset of detrimental health effects is a concern as obesity can influence the development of type 2 diabetes (T2DM) (2–5) and cardiovascular disease (CVD) (6, 7) later in life. As obese children are likely to become obese adults (8), it is important to characterize obesity and cardiometabolic profiles in young adults as they are at the forefront of the obesity epidemic and have greater risk to obesity-related health consequences. Apart from traditional obesity risk factors of poor diet, low physical activity, and low socioeconomic status (SES), epidemiological evidence has shown that air pollution may contribute to increased risk for obesity (9–12) and cardiometabolic disease (13–17). Furthermore, several studies have shown stronger associations with air pollution and adverse cardiovascular health in obese subjects compared to normal weigh subjects suggesting that obesity status may exacerbate the effects of air pollution (15, 18). Research on the effects of air pollution on obesity and cardiometabolic outcomes focused on the young adulthood period, however, is lacking in the literature.

Our current study, the Meta-AIR (Metabolic and Asthma Incidence Research) study, is a subset of young adults aged 17–22 years from the larger Southern California Children's Health Study (CHS). We examined associations of prior 1-month (short-term) and prior 1-

year (long-term) air pollution exposures on various indicators of obesity and cardiometabolic health. Regional ambient pollutants explored include nitrogen dioxide (NO2), ozone (O3), particulate matter with aerodynamic diameter <10 μm (PM10), and particulate matter with aerodynamic diameter <2.5 μm (PM2.5), and near-roadway air pollution (NRAP) include freeway, non-freeway, and total nitrogen oxides (NO_x) . The aim of this study was to determine if prior 1-month or 1- year ambient and NRAP exposures are associated with obesity measures and cardiometabolic outcomes in young adults. We hypothesized that increased exposure to prior 1-month and 1-year ambient and NRAP will be associated with higher levels of adiposity measures and adverse levels of cardiometabolic outcomes.

2. Material and Methods

2.1. Study Recruitment

The Meta-AIR study is a subset of young adults aged 17–22 years who were originally part of the larger CHS. Details of the CHS have been described previously (19). Briefly, in 2002 a cohort of kindergarten and first grade children were recruited from public schools across Southern California communities and followed through their high school years. Meta-AIR subjects were selected based on their high school overweight or obese status in 2011–2012 of CHS as well as predicted NOx exposures from their respective residential addresses in CHS towns. Potential participants were oversampled from "low" and "high" predicted NOx exposures to ensure maximum exposure contrast amongst study subjects within each CHS Southern California community. This recruitment strategy allowed for a wide range of air pollution exposures amongst potentially overweight and obese CHS young adults. Inclusion criteria included age- and sex-specific BMI percentiles $85th$ percentile measured by CHS staff in school year 2011–2012. Exclusion criteria were as follows: ineligible if using any medications known to influence body composition and insulin action/secretion, any diagnosis of diseases that may influence insulin or body composition including Type 1 and Type 2 diabetes, and any major illness since birth. Eligible participants, who are now young adults, were contacted and invited to enroll in the Meta-AIR study between 2014–2018. Written informed assents and consents were obtained from study participants. The Institutional Review Board at the University of Southern California approved this study.

2.2. Study Design

The Meta-AIR study visit included several questionnaires as well as extensive phenotyping of obesity and cardiometabolic outcomes conducted at the University of Southern California Diabetes and Obesity Research Institute and the Clinical Trials Unit from 2014–2018. The study visit flow is shown in Figure 1. In short, we administered questionnaires detailing sociodemographic characteristics, parental health and education, smoking history including e-cigarette use, self-reported physical activity, residential history, and 24-hour diet recalls (20). The first dietary recall was completed in person at the study visit, and the second was conducted by phone. A third phone recall was conducted if one of the first two recalls was either "more than usual" or "less than usual" from what the participant usually consumes day to day. These diet data were processed using the Nutrition Data System for Research

(version 2014, University of Minnesota). Details of adiposity and cardiometabolic measures obtained are below.

2.3. Adiposity and Cardiometabolic Outcomes

2.3.1. Adiposity—Several anthropometric and body composition measures were taken to estimate adiposity: 1) height and weight to determine body mass index (BMI) where BMI= weight/height² (kg/m²), 2) dual-energy X-ray absorptiometry (DEXA) scan to determine total body fat percent, and 3) 3T magnetic resonance imaging (MRI) abdominal scan to determine subcutaneous abdominal adipose tissue (SAAT), visceral adipose tissue (VAT), and hepatic fat fraction (HFF). Obesity was defined as BMI 30 kg/m^2 and nonobesity defined as BMI <30.0 kg/m².

2.3.2. Glucose and lipid metabolism—Following a minimum 10-hour fast, a 2-hour oral glucose tolerance test (OGTT) was administered using a load of anhydrous glucose dissolved in water for 1.75 grams per kilogram of body weight with a max dose of 75 grams. All participants received the maximum glucose load. Blood glucose and insulin samples were collected at fasting (pre-glucose load) and then post glucose challenge at 30-, 60-, 90-, and 120-minutes. Glucose-related outcomes included fasting glucose, fasting insulin, insulin area under the curve (AUC), homeostatic model assessment for insulin resistance (HOMA-IR), and the Matsuda Index. Insulin AUC was calculated using the trapezoidal method using all time points from the OGTT. HOMA-IR gives estimates of insulin resistance (IR) from fasting insulin and glucose concentrations where $HOMA - IR = \frac{fasting \ glucose * fasting \ insulin}{405}$ 405

(21). The Matsuda Index gives an approximation of whole-body insulin sensitivity using all times points from the OGTT were the ratio of plasma glucose to insulin concentrations are calculated.

Matsuda index is defined as
$$
\frac{1000}{\sqrt{glucose}_{fasting} * insulin_{fasting} * A * B}
$$
 such that

= *glucose f asting* ∗ 15 + *glucose* 30min ∗ 30 + *glucose* 60min ∗ 30 + *glucose* 90min ∗ 30 + *glucose* 120min ∗ 15 120

 $B =$ *insulin f asting* ∗ 15 + *insulin* 30min ∗ 30 + *insulin* 60min ∗ 30 + *insulin* 90min ∗ 30 + *insulin* 120min ∗ 15 $\overline{120}$

(22). Fasting lipid-related outcomes included triglycerides, total cholesterol, high-density lipoprotein (HDL), low-density lipoprotein (LDL), and very-low-density lipoprotein (VLDL) cholesterols.

2.4. Assays

and

Blood samples from the OGTT were collected in potassium oxalate, sodium fluoride 2mL tubes and centrifuged for 15 minutes at 1500 RCF. These plasma samples were then assayed for glucose concentration by hexokinase-mediated reaction assay run on Roche Covas C501. Additional OGTT samples were collected in sodium heparin 2mL tubes for insulin and centrifuged at 2500 RPM for 10 minutes. Plasma samples were stored at −80°C and later assayed for insulin in duplicate by Human Insulin ELISA Kit (EZHI-14BK). Fasting blood

for lipids was collected in serum separator 4mL tube, inverted several times, placed in room temperature for 60 minutes for clotting and centrifuged at 2000 RPM for 10 minutes. Serum lipid samples were stored at −80°C and later assayed in duplicate by Fujifilm Wako Diagnostics enzymatic assay.

2.5. Air Pollution Exposures

Residential history was collected from all Meta-AIR participants at their study visit including move in and move out dates for each respective residence. Residential addresses were geocoded using the Texas A&M geocoder (23) and assigned latitude and longitude coordinates that reflect each subject's housing unit or building. Monthly air pollution data was averaged for prior 1-month and 1-year regional ambient and near-roadway air pollution (NRAP) exposures to reflect short-term and long-term exposures prior to each participant's study visit. Exposures were weighted by time spent at each different residential address by month since some of our Meta-AIR participants were college students who lived between two residences during the year. In these instances, short-term and long-term exposures prior to the study visit accounted for both college and parental home residences using move in and move out months to appropriately weigh time spent at each respective residence. Additionally, our analysis included historic air pollution exposures or cumulative childhood exposures that were obtained from the parent study CHS, which account for past exposures beyond our periods of interests: prior 1-month and 1-year. For regional ambient pollutants, historic air pollution was defined as average childhood exposures for each participant from birth through year 2011. For NRAP, historic air pollution exposure was defined as average childhood exposures from CHS study entry (May 2003) through year 2011 where all our study participants had NRAP data available.

2.5.1. Ambient Air Pollution Exposures—Regional exposures were obtained from ambient monitoring stations by downloading hourly air quality data from the U.S. Environmental Protection Agency's Air Quality System [\(http://www.epa.gov/ttn/airs/](http://www.epa.gov/ttn/airs/airsaqs) [airsaqs\)](http://www.epa.gov/ttn/airs/airsaqs). Daily averages for four regional ambient air pollutants, $NO₂, O₃, PM₁₀$, and $PM_{2.5}$, were calculated. For O_3 only, levels were characterized as the eight-hour average daily maximum concentrations. Air monitoring stations in California are spaced 20–30 kilometers (km) apart, which provides good characterization of air pollution gradients across the region. Gaseous pollutants like $NO₂$ and $O₃$ are measured by the Federal Reference Method (FRM) monitors while particulates like PM_{10} and $PM_{2.5}$ are measured through FRM and Federal Equivalent Method (FEM) monitors. Monthly averages were calculated from daily data using 75% completeness criteria. To calculate monthly ambient exposures, parcel level data was used in the inverse distance-squared weighting algorithm which spatially interpolated air quality data from up to four monitoring stations within a 50 km radius of the participant's residence (24).

2.5.2. Near-Roadway Air Pollution Exposures—NRAP exposures were estimated by the California Line Source Dispersion Model (CALINE4) through detailed residential history where each participant's residential addresses were geocoded. CALINE4 line-source dispersion model then estimated concentrations of near-road NO_x at each latitude and longitude for freeway and non-freeway roads using traffic emissions (calculated within 5-km

buffer of the residence), traffic volume, roadway geometry and meteorological conditions including wind speed and direction, pollution mixing heights, and atmospheric stability (25). Traffic counts and road geometry were obtained from Caltrans and TeleAtlas/GDT, and average daily traffic volumes were assigned based on year. Monthly near-road freeway, nonfreeway and total NO_x (sum of freeway and non-freeway) were then calculated for 1-month (short-term) and 1-year (long-term) average NRAP exposures prior to the study visit

2.6. Statistical Methods

Physical and cardiometabolic characteristics of the cohort were compared by obesity status (non-obese vs obese) using chi-square or t-tests. Non-obesity was defined as BMI <30.0 kg/m^2 and obesity as BMI 30.0 kg/m². All outcomes were assessed for normality and skewed measures were log transformed to fit a normal distribution. Triglycerides, VLDLcholesterol, fasting insulin, HOMA-IR, Matsuda Index were log transformed to meet assumptions of the linear regression. One subject was removed from this analysis due to undiagnosed diabetes; another subject was removed from the glucose-related cardiometabolic analysis due to a high fasting insulin that was greater than 4 standard deviations (SDs) above the mean.

Linear regression models were used to estimate effects of short-term (1-month) and longterm (1-year) air pollution exposures prior to study visit on obesity and cardiometabolic measures. Models were adjusted for age, sex, race/ethnicity, occupational status of participant (SES surrogate), parental education (SES surrogate), self-reported exercise, current cigarette smoking, e-cigarette use, body fat percent, diet (average total calories per day), season of study visit (warm or cool), historic air pollution exposure, and baseline CHS town as a random effect. Historic air pollution data, or cumulative childhood exposures, allows us to evaluate the effects of short- and long-term exposures on obesity- and cardiometabolic-related outcomes independent of past childhood air pollution exposures. Given we had this data available from the parent CHS study, we included these historic exposures to be able to account for the more recent short-term or long-term exposures of interest. Besides near-road non-freeway and total NO_x , historic air pollution exposures have low to median correlation with prior 1-month or 1-year average air pollution exposures (all spearman correlation coefficient 0.7, Supplement Table 2). Association estimates of air pollution exposure and obesity- and cardiometabolic-related outcomes are reported for a 1 SD in air pollution exposure for prior 1-month and 1-year average regional ambient and NRAP exposures. We also investigated whether the associations between air pollution exposure and metabolic outcomes differed by sex, race/ethnicity and obesity status by testing the interaction terms in the full model. Additionally, we further explored associations with multipollutant models with additional short-term pollutants in short-term associations as well as additional long-term pollutants in long-term air pollution exposure associations. A two-sided p -value < 0.05 was considered statistically significant for all models. All analyses were performed in SAS, version 9.4 (SAS, Institute, Cary, NC).

3. Results

From 2014–2018, the Meta-AIR study enrolled 158 young adults who underwent extensive obesity and cardiometabolic phenotyping. General study characteristics are presented in Table 1. Briefly, mean age of participants was 19.7 years (SD=1.2, range=17.6–22.9). There were slightly more males than females (52.5% vs 47.5%), and 60% of participants were Hispanic, 28% were Non-Hispanic White and remaining 13% of participants were Asian, African American or other/mixed races. Generally, participants were full-time college students, students with part time/full time jobs, or working full time. Approximately 80% of participant's parents had education levels of high school graduation and beyond. About 6% of participants were current smokers who have smoked 20 cigarettes or more in the past month, and e-cigarette ever use was about 15% amongst study participants. Our participants consumed an average of 2050 kcal (SD=632) per day obtained from the dietary recalls. Sociodemographic characteristics did not differ by obesity status (non-obese vs obese) across all variables (all p>0.1, Table 1).

Mean adiposity- and cardiometabolic-related outcomes amongst all Meta-AIR participants as well as by obesity status are shown in Table 2. Of the 158 participants, 37% were obese $(n=59)$ with BMI 30 kg/m², 47% were overweight $(n=75)$ with 25 kg/m² BMI< 30 kg/m², and 15% had normal BMI (n=24) with BMI<25 kg/m². Amongst all study participants, mean BMI was 29.9 kg/m² (SD=5.1) and mean body fat percent was 34.9% (SD=8.5). As expected, obesity-related measures (BMI, total body fat percent, SAAT, VAT, and HFF) were higher in obese compared to non-obese participants, all p<0.0001 (Table 2). Cardiometabolic measures were classified into two groups: lipid and glucose metabolism. For lipid metabolism, means for fasting lipid measures are presented in Table 2. Higher levels of triglycerides and VLDL-cholesterol are seen in obese versus non-obese subjects (p=0.0004); furthermore, lower HDL-cholesterol levels were seen in obese compared to nonobese subjects (p=0.006). Total cholesterol and LDL-cholesterol levels were similar across non-obese and obese subjects (p=0.6 and 0.7, respectively). Details of glucose metabolism measures are found in Table 2. Higher levels of glucose-related metabolic measures, like fasting glucose and fasting insulin, are seen in obese compared to non-obese participants, all p<0.01. Compared to the non-obese participants, obese participants show early signs of insulin resistance with higher HOMA-IR (3.2 in obese vs 1.5 in non-obese) and lower Matsuda index levels (3.9 in obese vs 7.3 in non-obese) (Table 2). In adults, the HOMA cutoff point for IR is >2.5 (21); however studies in children and adolescents have proposed higher cut off points >3.16 (26) and >4.0 (27). The Matsuda Index 2.5 has been proposed as the cut off for IR (28).

Prior to study visit, 1-month and 1-year average regional ambient and NRAP exposures are shown in Table 3, and historic exposures are show in Supplemental Table 1. To avoid potential collinearity of 1-month vs historic or 1-year vs historic air pollution exposures in the same model, Spearman correlations between 1-month vs historic exposures and 1-year vs historic exposures are shown in Supplemental Table 2. All regional ambient models $(NO₂, O₃, PM₁₀, and PM_{2.5})$ for 1-month and 1-year average air pollution exposures included the historic exposures (all correlations<0.7). For NRAP models (freeway, non-

freeway, total NO_x), freeway NO_x was the only NRAP exposure that included the historic exposures in the 1-month and 1-year NRAP models (correlation<0.7).

3.1. Associations of Short- and Long-Term Ambient Air Pollution and Obesity-Related Outcomes

Associations of short-term (1-month) and long-term (1-year) average ambient air pollution exposures and obesity-related outcomes are shown in Table 4. All models reflect association estimates for one obesity outcome and one short-term or long-term ambient air pollutant adjusting for age, sex, race/ethnicity, occupational status of participant, parental education, self-reported exercise, current cigarette smoking, e-cigarette use, total body fat % (not included in SAAT, VAT, HFF models), diet, season of visit, and respective historic air pollution exposures. In models pertaining to adiposity measures of total body fat percent and abdominal adiposity (SAAT, VAT, and HFF), we found prior 1-month O_3 exposure was statistically, significantly associated with HFF, liver fat. A 1 SD (14.1 ppb) increase in prior 1-month O_3 exposure was associated with a 20% higher liver fat levels after adjusting for covariates $(p=0.02)$ (Table 4). We further explored the association between liver fat and short-term O_3 exposure in multipollutant models where short-term NO_2 or short-term PM_2 . were added separately to the model as these pollutants were not highly correlated with shortterm O_3 (Supplemental Table 3). Association estimates were slightly attenuated by adding short-term $NO₂$ or $PM_{2.5}$, however associations remained statistically significant (Supplemental Table 5). The association between HFF and short-term O_3 was not modified by sex (male vs female), Hispanicity (non-hispanic white vs hispanic), or obesity status (obese vs non-obese) (all $p_{interaction} > 0.1$). We did not find any other statistically significant associations of BMI, total body fat percent, SAAT, or VAT and short- or long-term ambient measures of NO_2 , O_3 , PM_{10} , and $PM_{2.5}$.

3.2. Associations of Short-Term Ambient Air Pollution and Cardiometabolic-Related Outcomes

Associations with short-term, prior 1-month, ambient pollutant exposures and cardiometabolic measures are shown in Table 5. Amongst lipid metabolism measures, statistically significant associations with higher short-term O_3 exposures and higher triglycerides, higher VLDL-cholesterol, and lower HDL-cholesterol levels were found after adjusting for covariates (all $p<0.05$, Table 5). For example, a 1 SD (14.1 ppb) increase in prior 1-month O_3 exposure was associated with a 18% higher triglyceride levels (p=0.04) and a 18% higher VLDL-cholesterol levels (p=0.04). Additionally, a 1 SD increase in prior 1-month O_3 exposure was associated with a 3.02 mg/dL lower HDL levels after adjusting for covariates (p=0.03).

We further explored short-term O_3 and lipid associations in multipollutant models by adding short-term $NO₂$ or short-term $PM_{2.5}$ (Supplemental Table 5). In multipollutant models with short-term O_3 and NO_2 , there was slight attenuation in association estimates across triglycerides, HDL-cholesterol and VLDL-cholesterol but all associations remained statistically significant (all p<0.05). With short-term O_3 and $PM_{2.5}$, association estimates were also attenuated, however triglyceride and VLDL-cholesterol models were no longer statistically significant (p=0.09 and p=0.09, respectively). Effect modification by sex,

Hispanicity, and obesity status for triglycerides, HDL-cholesterol, and VLDL-cholesterol models were further explored however there were no statistically significant interactions were found (all $p_{interaction} > 0.1$). No other statistically significant associations were found with short-term ambient pollution exposures, NO_2 , PM_{10} , and $PM_{2.5}$, and lipid metabolism measures. Glucose metabolism measures of fasting glucose, fasting insulin, insulin AUC, HOMA-IR and Matsuda Index were not associated with short-term ambient pollutants.

3.3 Associations of Long-Term Ambient Air Pollution and Cardiometabolic-Related Outcomes

Associations of long-term, prior 1-year, ambient pollution exposures and cardiometabolic measures are shown in Table 6. Amongst lipid metabolism measures, higher long-term ambient $NO₂$ exposure was associated with higher fasting total cholesterol and LDLcholesterol levels in this cohort of young adults (Table 6). For example, a 1 SD (3.9 ppb) increase in 1-year average $NO₂$ exposure was associated with 11.3 mg/dL higher total cholesterol levels after adjusting for covariates (p=0.04). Similarly, a 1 SD increase in 1-year $NO₂$ exposure was associated with a 9.4 mg/dL higher LDL-cholesterol levels (p=0.04). Additional exploration with multipollutant models was completed by adding long-term O_3 or long-term $PM_{2.5}$. (Supplemental Table 4). In multipollutant models with long-term $NO₂$ and long-term O_3 , associations were slightly attenuated in total cholesterol and LDLcholesterol models with marginal significance $(p=0.05$ and $p=0.06$, respectively) (Supplemental Table 6). In multipollutant models with long-term $NO₂$ and long-term $PM_{2.5}$, associations strengthened when adding long-term $PM_{2.5}$ in total cholesterol and LDLcholesterol models maintaining statistical significance p<0.05 (Supplemental Table 6).

Associations of long-term $NO₂$ exposure and total cholesterol and LDL-cholesterol were further assessed for effect modification by sex, Hispanicity, and obesity status. There were no statistically significant interactions of sex and hispancity (all p>0.1); however, the interaction for obesity status (non-obese vs obese) and $NO₂$ were statistically significant for total cholesterol ($p=0.008$) and LDL-cholesterol ($p=0.03$). These results suggest differences in the effect of long-term $NO₂$ exposure on lipid levels by obesity status, so associations were stratified by obesity status. In obese subjects, the association estimate of prior 1-year NO2 exposure on total cholesterol and LDL-cholesterol were substantially higher compared to non-obese subjects (Figure 2). The association estimates between prior 1-year $NO₂$ exposure and total cholesterol among obese participants were nearly 5-fold larger (21.4 mg/dL vs 4.7 mg/dL) than non-obese participants. Likewise, the association estimates between prior 1-year NO₂ exposure and LDL-cholesterol among obese participants were 9fold larger (19.9 mg/dL vs 2.2 mg/dL) than non-obese participants.

Amongst glucose metabolism measures, higher long-term $PM_{2.5}$ exposure was associated with higher insulin AUC such that a 1 SD (2.5 μ g/m³) increase in prior 1-year PM_{2.5} exposure was associated with 33.6 higher units of insulin AUC (p=0.03). Further exploration was conducted with multipollutant models adding long-term $NO₂$ or long-term $O₃$ (Supplemental Table 4). In the multipollutant model with long-term $PM_{2.5}$ and NO₂, the association with insulin AUC was attenuated and was no longer statistically significant (p=0.09, Supplemental Table 7). Similarly, the multipollutant model with long-term PM_2 .

and O_3 , further attenuation was found with loss in significance ($p=0.17$, Supplemental Table 7). There was no effect modification with insulin AUC and long-term $PM_{2.5}$ exposure by sex, Hispanicity, and obesity status ($p_{interaction} > 0.1$). There were no other statistically significant associations between long-term ambient exposures, NO_2 , O_3 , PM_{10} , and $PM_{2.5}$, and glucose metabolism measures of fasting glucose, fasting insulin, insulin AUC, HOMA-IR, and Matsuda Index.

3.4 Associations of Long-Term and Short-Term NRAP and Obesity- and Cardiometabolic-Related Outcomes

Like regional ambient air pollution exposures, associations of short-term and long-term NRAP exposures with obesity- and cardiometabolic-related outcomes were explored (Supplemental Table 8–9). There were no statistically significant associations with prior 1 month and 1-year average NRAP exposures of non-freeway, freeway and total NO_x with obesity- or cardiometabolic-related outcomes.

4. Discussion

In the Meta-AIR study, we conducted a comprehensive analysis with short- and long-term regional ambient and NRAP exposures (in both single- and multi-pollutant models) and obesity- and cardiometabolic-related outcomes and found associations with only a few outcomes. These associations include liver fat (with short-term O_3), lipid profiles (with short-term O_3 and long-term NO_2) and insulin-related phenotype (with long-term $PM_{2.5}$). Though we did not find statistically significant associations with short-term or long-term ambient and NRAP exposures and BMI and other adiposity measures, we showed a positive association where higher short-term (prior 1-month) O_3 exposure was associated with higher liver fat in young adults. Increasing incidence of non-alcoholic fatty liver disease (NAFLD), an accumulation of liver fat, has been strongly liked to obesity, and many with NAFLD are obese and insulin resistant which draws concerns (29). Additionally, there is some evidence of the role of air pollution on NAFLD (30).

Our findings suggest that higher short-term O_3 and higher long-term NO_2 exposures may increase risk of dyslipidemia in young adults. Though it is not clear why higher short-term O_3 and higher long-term NO_2 exposures affects different lipid types, perhaps some ambient pollutants like O_3 elicit acute or short-term effects whereas NO_2 exposures may have more chronic or long-term effects on lipid profiles. Several reported associations support our study findings, however most studies have focused effects of air pollution and lipid abnormalities in adult and elderly populations (31–34). Similar to our findings, a recent study of 15,000 Chinese adults (aged 18–74 years) detected statistically significant associations with increased long-term ambient air pollution exposures and altered lipid measures with stronger associations in obese participants (34). Studies in young adults are lacking, though one study in youth has shown deleterious effects of poor air quality and elevated levels of total cholesterol and triglycerides in Irani adolescents (35). Additionally, an experimental model has shown that increased air pollution exposure may perturb lipid levels (36), though exact biological mechanism remains uncertain. One proposed mechanism is inflammatory responses from air pollution exposure which induces macrophage infiltration in adipose

tissue (37). Macrophage infiltration then cues expression of proinflammatory cytokines inducing uncontrolled lipolysis which may lead to elevated levels of circulating nonesterified fatty acids (38). These fatty acids are transported to the liver for upregulation of triglycerides synthesis, VLDL production and ultimately dyslipidemia.

Lastly, associations of air pollution and glucose metabolism in children and adolescents have been shown previously (13, 39, 40); yet again, studies are limited in young adults. One study from Southern California showed adverse effects of higher $NO₂$ and $PM₂$, exposures on insulin sensitivity and beta-cell function in overweight and obese children (aged 8–15 years) after an average 3 year follow up period (13). Though we did not find statistically significant associations with short-term ambient and NRAP exposures and glucose metabolism measures, our study suggests higher long-term (prior 1-year) $PM_{2.5}$ exposure may be associated with higher insulin AUC levels. Several animal models have proposed mechanisms by which air pollution may affect glucose metabolism (37, 41).

The Meta-AIR study has notable strengths. Unlike most air pollution studies, our study had life-time residential history on our participants by which we were able to incorporate past, childhood air pollution exposures. We used the well-established CHS to recruit our Meta-AIR participants where we sampled across high and low air pollution exposures across CHS communities to ensure a wide range of air pollution exposures in both regional ambient and NRAP exposures. An extensive number of exposure metrics (both short- and long-term regional and local traffic pollutants) alongside various measures of adiposity and cardiometabolic health were carried out in this study. A rigorous collection of adiposity measures using gold-standards such as DEXA and MRI and cardiometabolic-related outcomes were performed prospectively. We collected many different measures of modifiable risk factors such as diet, physical activity, current smoking and e-cigarette use, and non-modifiable risk factors age, race/ethnicity, sex, occupational status of participant and parental education via questionnaires. Our air pollution exposure estimates incorporated multiple residences as our study population included college-aged subjects who resided at their parent's residence as well as their school residence giving appropriate weights to each respective residence.

Despite the strengths, there were limitations to this current study. First, we cannot draw causal relationships between air pollution exposures and obesity- and cardiometabolicrelated outcomes as our study outcomes were only collected at one time point. We were limited in our sample size as we only had 158 young adults in this study; therefore, various interactions tested should be interpreted with caution. Given our study design, our participants were primed for potentially adverse levels of obesity and cardiometabolic outcomes, however given the standard deviations of our clinical measures, there was an adequate range of outcomes. There were no contextual variables in our analysis given that ~70% of our participants were students (full time or part time), about half lived in multiple residences due to school addresses and parental addresses (time spent in summer and winter break months). Contextual covariates would need to incorporate several different addresses, weighting time spent at in each neighborhood as most student who lived in college dorms or apartment were not in their hometowns. Though this may be feasible, we collected a rather robust list of individual-level covariates that may capture this information. Despite

incorporating multiple residences, we were unable to incorporate other locations such as work locations that our subjects may have frequently visited or indoor exposures. We also acknowledge our variables of occupational status of the participant and parental education may not capture SES fully. Our study findings may be only generalizable to young adults with similar demographic data (primarily Hispanic or White), with similar range of air pollution exposures, and those with a history of overweight/obesity during mid-teenage years. Additionally, markers of oxidation were not available in this current study. Finally, our findings cannot determine the precise mechanism behind the association of air pollution and obesity and cardiometabolic health, however our results indicate potential pathways that may involve disrupted lipid metabolism, increased liver fat and increased insulin production.

5. Conclusion

Findings from the Meta-AIR study suggests that differential ambient regional air pollution exposures, NO_2 , O_3 and $PM_{2,5}$, may contribute to poor cardiometabolic health in young adults aged $17-22$ years. Notably, the association between long-term $NO₂$ and fasting lipid measures may adversely affect obese young adults compared to non-obese young adults. Differences in association by obesity status suggest that obese young adults may be more susceptible to adverse effects of long-term air pollution exposure, and this may exacerbate indicators of cardiometabolic health. Additional longitudinal studies in young adults are warranted as to verify associations of air pollution and adverse obesity and cardiometabolic outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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- We assessed measures of adiposity, cardiometabolic health in 158 young adults.
- **•** Ambient air pollution was associated with some cardiometabolic risk factors.
- Long-term NO₂ was associated higher total cholesterol and LDL-C levels.
- Associations between NO₂ and lipids were more pronounced in obese participants.
- Short-term O₃ was associated with higher triglycerides and VLDL-C and lower HDL-C.

Figure 1. Meta-AIR Study^a Flow

^aMeta-AIR subjects were recruited between 2014–2018 from Children's Health Study to examine the effects of short- and long-term ambient and near-roadway air pollution exposures on obesity and cardiometabolic health in young adults.

Figure 2. Associations^a of Prior 1-Year NO2 Exposures and Lipid Metabolism Measures by Obesity Status in 158 Participants Enrolled in the Meta-AIR Study from 2014–2018. $NO₂=$ nitrogen dioxide; HDL= high-density lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein; obese= BMI 30.0 kg/m^2 , non-obese= BMI< 30.0 $kg/m²$.

^aAssociations reflect change in outcome measure (association estimate $(β)$) scaled to 1 standard deviation of prior 1-year average ambient $NO₂$ with 3.9 ppb stratified by obesity status (non-obese vs obese).

^bLinear regression model was used to estimate the associations of 1-year $NO₂$ and lipid metabolism outcomes after adjusting for age, sex, race/ethnicity, occupational status of subject, parental education, self-reported exercise, current cigarette smoking, e-cigarette use, total body fat percent, diet, season, and historic air pollution exposure. $*p<0.05$

Table 1.

Sociodemographic Characteristics by Obesity Status of 158 Participants Enrolled in the Meta-AIR Study from 2014–2018.

 α Variable denominators may differ due to missing values.

 b Non-Obese= BMI<30.

 c Obese= BMI 30.

d Chi-square (non-obese vs obese) p-value.

 e^{θ} Other races= Asian (n=10), African-American (n=6), Other/Mixed Races=(n=4).

 $f_{\text{Current smoker}}$ smoker smoked more than 20 cigarettes (1 pack) in the past month.

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SD= standard deviation; BMI=body mass index; MRI=magnetic resonance imaging; SAAT= subcutaneous abdominal adipose tissue; VAT=visceral adipose tissue; HFF= Hepatic (Liver) Fat Fraction; adipose tissue; HFF= Hepatic (Liver) Fat Fraction; AUC= area under the curve; HOMA-IR= homeostatic model assessment-insulin resistance; HDL= high-density lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein. AUC= area under the curve; HOMA-IR= homeostatic model assessment-insulin resistance; HDL= high-density lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein. $\mathop{\mathrm{nce}}\nolimits$ imaging; $\mathop{\mathrm{S}}\nolimits$ $\mathop{\mathrm{A}}\nolimits$ SD= standard deviation; BMI=body mass index; MRI=mag

Non-Obese= BMI<30 where 24 participants have normal BMI (BMI<25) and 75 participants were overweight (25 BMI<30). Non-Obese= BMI<30 where 24 participants have normal BMI (BMI<25) and 75 participants were overweight (25≤BMI<30).

 $b_{\text{Obese}=BMI}$ 30. Obese= BMI ≥ 30.

 $c_{\text{T-test}}$ (non-obese vs obese) p-value. T-test (non-obese vs obese) p-value.

* one diabetic subject was removed

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Table 2.

Obesity and Cardiometabolic Measures by Obesity Status in 158 Participants Enrolled in the Meta-AIR Study from 2014–2018.

Obesity and Cardiometabolic Measures by Obesity Status in 158 Participants Enrolled in the Meta-AIR Study from 2014-2018.

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one subject with high fasting insulin removed.

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Table 3.

Short- and Long-Term Regional Ambient and Near-Roadway Air Pollution Exposures Among 158 Participants Enrolled in the Meta-AIR Study from 2014–2018.

SD=standard deviation; IQR=interquartile range; NO2= nitrogen dioxide; O3=ozone 8-hour maximum daily; PM10= particulate matter with aerodynamic diameter <10 μm; PM2.5=particulate matter with aerodynamic diameter <2.5 μm; ppb=parts per billion; NO_X=nitrogen oxides.

 $a¹$ -month average air pollution exposure prior to the Meta-AIR visit date.

 $b₁$ -year average air pollution exposure prior to the Meta-AIR visit date.

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ethnicity, occupational status of subject, parental education, self-reported exercise, current cigarette smoking, e-cigarette use (ever/never), total body fat % (not included in SAAT, VAT, HFF models), diet

ethnicity, occupational status of subject, parental education, self-reported exercise, current cigarette smoking, e-cigarette use (ever/never), total body fat % (not included in SAAT, VAT, HFF models), diet
(total calories

(total calories), season (warm/cool), and historic air pollution exposure.

Table 4.

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log-transformed variable

* p<0.05.

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^a of Short-Term Ambient Air Pollution Exposures with Cardiometabolic Measures in 158 Participants Enrolled in the Meta-AIR Study from Associations^a of Short-Term Ambient Air Pollution Exposures with Cardiometabolic Measures in 158 Participants Enrolled in the Meta-AIR Study from $2014 - 2018$ 2014–2018.

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iculate matter with aerodynamic diameter \triangle .5 μ m; HDL= high-NO2= nitrogen dioxide; O3=ozone 8-hour maximum daily; PM10= particulate matter with aerodynamic diameter <10 μm; PM2.5=particulate matter with aerodynamic diameter <2.5 μm; HDL= highdensity lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein; AUC= area under the curve; HOMA-IR= Homeostatic model assessment-insulin resistance. density lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein; AUC= area under the curve; HOMA-IR= Homeostatic model assessment-insulin resistance.

 A associations reflect change in outcome measure (effect estimate (β)) scaled to 1 standard deviation of prior 1-month average ambient NO2 with 5.7 ppb, O3 with 14.1 ppb, PM₁₀ with 9.7 µg/m³, and Associations reflect change in outcome measure (effect estimate (β)) scaled to 1 standard deviation of prior 1-month average ambient NO2 with 5.7 ppb, O3 with 14.1 ppb, PM₁₀ with 9.7 μg/m³, and PM2.5 with 4.3 μ g/m³. PM2.5 with $4.3 \,\mu\text{g/m}^3$.

occupational status of participant, parental education, self-reported exercise, current cigarette use, e-cigarette use (ever/never), total body fat %, diet (total calories), season (warm/cool), and childhood air occupational status of participant, parental education, self-reported exercise, current cigarette use, e-cigarette use (ever/never), total body fat %, diet (total calories), season (warm/cool), and childhood air b inear regression model used to estimate the associations of prior 1-month NO2, O3, PM10, and PM2.5 exposures with glucose- and lipid-related measures after adjusting for age, sex, race/ethnicity, Linear regression model used to estimate the associations of prior 1-month NO2, O3, PM10, and PM2.5 exposures with glucose- and lipid-related measures after adjusting for age, sex, race/ethnicity, pollution exposure. pollution exposure.

 $\dot{r}_{\rm log\text{-}transformed\ variable}$ log-transformed variable

 $*$ p<0.05.

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Associations^a of <u>Long-Term Regional Ambient Air Pollution</u> Exposures with <u>Cardiometabolic Measures</u> in 158 Participants Enrolled in the Meta-AIR
Study from 2014–2018. ^a of Long-Term Regional Ambient Air Pollution Exposures with Cardiometabolic Measures in 158 Participants Enrolled in the Meta-AIR Study from 2014–2018.

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particulate matter with aerodynamic diameter <2.5 µm; HDL= high-NO2= nitrogen dioxide; O3=ozone 8-hour maximum daily; PM10= particulate matter with aerodynamic diameter <10 μm; PM2.5=particulate matter with aerodynamic diameter <2.5 μm; HDL= highdensity lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein; AUC= area under the curve; HOMA-IR= homeostatic model assessment-insulin resistance. density lipoprotein; LDL= low-density lipoprotein; VLDL= very low-density lipoprotein; AUC= area under the curve; HOMA-IR= homeostatic model assessment-insulin resistance. י לי $\frac{1}{2}$ ية
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Associations reflect change in outcome measure (effect estimate (B)) scaled to 1 standard deviation of prior 1-year average ambient NO₂ with 3.9 ppb, O3 with 6.5 ppb, PM10 with 7.9 µg/m³, and PM2.5 Associations reflect change in outcome measure (effect estimate (β)) scaled to 1 standard deviation of prior 1-year average ambient NO2 with 3.9 ppb, O3 with 6.5 ppb, PM10 with 7.9 μg/m³, and PM_{2.5} with 2.5 μ g/m³.

 h inear regression model was used to estimate the associations of prior 1-year NO₂, O₃, PM₁₀, and PM_{2.5} exposures with glucose- and lipid-related measures after adjusting for age, sex, race/ethnicity, Linear regression model was used to estimate the associations of prior 1-year NO2, O3, PM10, and PM2.5 exposures with glucose- and lipid-related measures after adjusting for age, sex, race/ethnicity, occupational status of participant, parental education, self-reported exercise, current cigarette use, e-cigarette use (ever/never), total body fat %, diet (total calories), season (warm/cool), and historic air occupational status of participant, parental education, self-reported exercise, current cigarette use, e-cigarette use (ever/never), total body fat %, diet (total calories), season (warm/cool), and historic air pollution exposure. pollution exposure.

 $\dot{r}_{\rm log\text{-}transformed\ variable}$ log-transformed variable

 $*$ p<0.05.