EXHIBIT A

SCOPE OF WORK

☒ Contract ☐ Grant

Does this project include Research (as defined in the UTC)? ☒ Yes ☐ No

PI Name: **Ying-Ying Meng**

Project Title: O_3 Exposure and Respiratory Effects – School absenteeism, Asthma-related Symptoms, and Asthma-related Emergency Department (ED) visits and Hospitalizations

Project Summary/Abstract

Despite great improvements in air quality control, ozone (O_3) remains a major concern for public health in the United States, especially in California. Although both short-term and long-term O_3 exposures have been linked to a range of adverse health impacts, very few studies investigated the impact of O_3 exposure on school absenteeism due to health issues and asthma symptoms. Additionally, the short-term and long-term effects of O_3 have not been enough investigated especially for short-term exposure due to the difficulty in modeling ozone exposure and the limited availability of health outcome data.

To investigate both short-term and long-term O_3 exposures on school absenteeism due to health issues and the frequency of asthma-related symptoms, the University of California Los Angeles (UCLA or Contractor) investigators will conduct a study linking the California Health Interview Survey (CHIS) 2011- 2019 data (including more than 10,000 teen and about 7000 child respondents, and more than 200,000 adults in California) to daily O_3, particulate matter with diameter 2.5 micrometers and smaller ($PM_{2.5}$) and nitrogen dioxide (NO_2) concentrations generated from the chemical transport model (CMT) developed by Dr, Michael Kleeman from the University of California, Davis - California Institute of Technology (UCD-CIT), based on the respondents' geo-coded residential addresses and interview dates.

With the linked data, the Contractor will perform several statistical analysis models including logistic and Poisson regression models to examine if the school absence and the frequency of asthma-related symptoms are associated with the short-term (e.g. daily, weekly, or monthly) or long-term (e.g. yearly average or seasonal such as August-October average) exposures to O_3 after controlling for covariates and co-pollutants such as $PM_{2.5}$ and NO_2. The Contractor will also conduct stratified and interaction analyses to identify whether the O_3-related health effects are different by subpopulations such as race/ethnicity, gender, and income groups. The Contractor will also perform sensitivity

analyses, such as different lag times for pollutant exposures, adjustments of various covariates, and matching samples for assessing the pollutant effect.

An investigation examining the impacts of O_3 exposure and health endpoints including school absenteeism and asthma-related symptoms is crucial to update and expand the California Air Resource Board's (CARB) ability to identify and quantify adverse effects of O_3 exposure for adults and children in California. The results of this project will help inform the policies, regulations, and strategies to emphasize the importance of strengthening O_3 standards, especially among vulnerable populations.

If Third-Party Confidential Information is to be provided by the State:

☐ Performance of the Scope of Work is anticipated to involve use of third-party Confidential Information and is subject to the terms of this Agreement; ***OR***

☐ A separate CNDA between the University and third-party is required by the third-party and is incorporated in this Agreement as Exhibit A7.

Scope of Work

Relying on the CHIS 2011-2019 data, the Contractor will investigate the adverse effects of both short-term and long-term O_3 exposure on school absenteeism and asthma-related symptoms, and possibly extend to other health outcomes such as asthma-related ED visits and hospitalization as well as work loss due to sickness in California. It would be crucial to update and expand the regulators' ability to identify and quantify adverse effects of O_3 exposure for adults and children in California, providing a better understanding of the full scope of health and welfare protections. The results of this project will help inform the policies, regulations, and strategies to strengthen O_3 standards, especially among vulnerable populations.

STATEMENT OF SIGNIFICANCE

Despite great improvements in air quality control, O_3 remains a major concern for public health in the United States, especially in California.[1] As a secondary gaseous air pollutant formed from traffic-related precursors under the influence of sunlight, tropospheric O_3 concentrations have continuously increased in the last century, especially in areas downwind of urban centers with dense populations[2] and high volumes of traffic. O_3 has been associated with a range of adverse health outcomes in observational studies[1, 3-5] There is an increasing recognition that there may be important variation in pollution and differential health effects within urban geographies,[6, 7] suggesting that more refined spatial or temporal monitoring may be informative for understanding health risks.[8]

Illness-related absences are common events representing a wide range of morbidity from mild transient illnesses to the most severe and prolonged illnesses that require ED visits or hospital admissions.[9] Children with asthma are particularly vulnerable to air pollution exposure.[8] Several studies have implicated ambient O_3 as a trigger of asthma symptoms or acute changes in lung function.[10-12] These populations may experience negative health impacts even when standards are met, and certain pollutants such as O_3 may be more responsible for the health effects.

According to the Technical Support Document (TSD) titled “Estimating $PM_{2.5}$- and Ozone-Attributable Health Benefits” (United States Environmental Protection Agency [U.S. EPA], 2023), the current evidence used to support U.S.EPA benefits analyses (BenMap) is limited.[13] The impact of O_3 exposure on school absenteeism due to health issues and asthma symptoms was only investigated by a limited number of studies. Illness-related school absenteeism is important but insufficiently studied outcomes in children, a group identified as especially sensitive to the adverse effects of ambient air pollution.[14] Currently, there is only one paper published in 2001 reporting that short-term O_3 exposure was associated with a substantial increase in school absences from both upper and lower respiratory illness,[15] and this study was conducted only among the children in 4th grade, not including the adolescents who are experiencing a period of physical and psychosocial changes that affect their health and well-being. The association between O_3 exposure and asthma symptoms was also under-studied and the results remain inconsistent. Lewis et al (2013)[8] studied the effects of short-term O_3 exposure on the frequency of asthma symptoms in an asthmatic population of primarily lower-income, African American, and Latino children (aged 5-12 years) in East and Southwest Detroit, MI. Both illness-related school absences and asthma symptoms are common events indicating an illness of sufficient severity to affect the child or adolescent’s daily functioning, as well as their family coping strategies.[16, 17]

Thus, there is an urgent need to update the quantification of adverse effects of O3 exposure in California, providing a quantified assessment of public health impacts of ambient O3, to promote a better understanding of the full scope of health and welfare protections from California’s air pollution regulations, programs, and policies. To fulfill these needs, the objectives of this proposed project are to:

1) Generate a thorough literature review regarding the adverse health effects associated with both long-term and short-term O_3 exposures, including but not limited to school absenteeism (all reasoned, health issues related, asthma-related), asthma symptoms and asthma-related emergency department visits and hospitalization, as well as the literature on O_3 effects in subgroups such as race/ethnicity, gender and income.
2) Develop and update air pollution data with a finer spatial resolution (4-km) which takes into account seasonal variations and complex O_3 chemistry, including O_3 precursor gases (VOCs and NOx), for estimating O_3 levels for the whole California state for the years 2011-2019.
3) Use the existing health data (CHIS) with the linkage of the updated refined O_3 exposure modeling approach to develop the C-R functions relating to O_3 exposure impacts on school absenteeism among children and asthma-related symptom occurrence among all the adults and children both statewide and subgroups such as race/ethnicity, gender and income.
4) Develop the concentration–response functions (C-R functions) to determine differential exposure and health impacts among children and adults, and examine how

socioeconomic factors (e.g. race/ethnicity, gender and income) affect vulnerability. It also includes identifying the exposure window(s) with high risk, the duration of the exposure (e.g. short- or long-term, or high peaks repeated over time), and whether there is a threshold or linear relationship between the exposure and health impacts.

5) To better understand the statewide health effects of O_3 exposure, additionally develop the C-R functions relating to short- and long-term O_3 exposure impacts on asthma-related ED visits and hospitalization among children and adults, as well as work loss due to sickness among adults both statewide and subgroups such as race/ethnicity, gender and income.

This research will provide CARB and U.S.EPA with updated information about exposure-response functions for both short-term and long-term O_3 exposures for the overall California population including both children and adults as well as vulnerable California communities and populations. The CARB and U.S.EPA will be able to determine where improvements in air quality standards may still be needed to reduce risk and ensure health equity, and which vulnerable communities or groups may be most affected and could be targeted for special interventions, in addition to informing stakeholders about the results. The results could also be used for updating U.S. EPA BenMAP health and economic burden estimates. These findings are essential for future studies and policy or community-based interventions.

BACKGROUND

O_3 is a secondary air pollutant mainly produced by chemical interactions involving solar radiation and O_3 precursors, such as nitrogen oxides (NOx), volatile organic compounds (VOC), and carbon monoxide (CO), which can be emitted from both natural and anthropogenic sources.[18, 19] Traditionally, these chemical reactions are known to depend on heat and sunlight, resulting in higher ambient O_3 concentrations.[18, 19] Particularly, during the warm season in California's metropolitan areas, it is common for O_3 concentrations to exceed health-protective standards.

Scientific evidence has linked O_3 to a range of adverse health impacts including cardiovascular and pulmonary diseases, and metabolic dysfunction.[4, 20, 21] It has been reported that exposures to O_3 at median or average levels near or even below the current eight hours (8-hour) National Ambient Air Quality Standard (NAAQS) and as low as 60 part per billion (ppb) were associated with adverse health outcomes, including declined lung function, asthma onset, and increased ED visits.[22-27]

Although the health effects of O_3 have been substantially investigated, while the results for certain health endpoints remain inconclusive, possibly due to the lack of well-developed O_3 exposure modeling and limited health outcome data.[28] Many studies use the O_3 concentration measured at community-level monitoring sites, making the studies can only be conducted within restricted areas (i.e. Lewis et al. studied only in two communities in Detroit, MI) and periods (i.e. Gilliland et al conducted the study only in the first six months in 1996), and consequently limiting the generalizability of the study results. Thus, the studies need to be updated with more recent and population-based data.

In the current BenMAP platform, for all school absences, the coefficient ($\beta = 0.0078$) and standard error (std = 0.0044) are calculated based on a percent increase of 16.3% (95% confidence interval [CI] -2.6%, 38.9%) associated with a 20-ppb increase in 8-hour average monitored O_3 concentration in the 12 communities in South California in the first six months of 1996 from Gilliand's study.[15] In this study, the Contractor will use the consecutive nine (9) years state-wide data from 2011-2019 by linking to the chemical transport model (CTM) model generated O_3 exposure with higher spatial resolution to calculate the coefficient (β_{O_3}) of the daily O_3 effect estimate (where exp (β_{O_3}) represents the odds ratio for school loss corresponding to per 1-ppb increase in short-term average (i.e. 1- to 4-week average) O_3 exposure prior to the interview date. Given the study population and advanced exposure assessment method, our study is more compliant with the criteria used by the U.S. EPA to identify studies and risk estimates to use in a benefits assessment, which is documented in the U.S. EPA Technical Support Document (TOC) 2022 Table 1.

Previously, Gilliland and Lewis used longitudinal cohorts to examine the O_3 impacts on school absenteeism and asthma symptoms, but their data on absence and symptoms were collected via a one-time survey over a limited period. These studies only examined O_3-related school absenteeism or asthma-related symptoms among the children in elementary schools in restricted areas (e.g. Gilliland et al. only studied school absenteeism among 4th graders in 12 southern California communities) and Lewis et al. studied only in two communities in Detroit, MI). Although the design of longitudinal data is well suited for stationary populations, both the standard longitudinal and rotating method of survey face possible attrition problems, which is a potentially serious source of bias, and attrition is known to occur more with some groups of people than with others. Every year, CHIS respondents are selected using the independent repeated cross-sectional sampling method to ensure enough new respondents are recruited, thus ensuring a steady level of reliability for each successive sample when under stable sampling conditions. Therefore, the consecutive CHIS survey data could be treated as a relatively stable population-based longitudinal cohort study, especially with a larger sample size of school-aged children (about 10,000) and teens (about 7,000 +) population, compared to the sample size in Gilliland's (2,068 4th grade children) and Lewis's (298 children 5-12 years) studies. CHIS interviewed not only child but also adolescent respondents besides adult respondents, which provides a large sample size for the school-age population. CHIS asked the school absences (all reasons, excluding vacation or home schooling), and CHIS also asked about missed school days due to health issues and asthma-related school absences, so that some sensitivity analyses can be done using the different health end-point measures. **Table 1** summarizes and compares the characteristics between previous studies (Gilliland et al. and Lewis et al.) and proposed study using CHIS data. CHIS data are also much better than school absenteeism data from the California Department of Education, which can only provide yearly-based data at the school level, and only categorize the absence into "excused" and "unexcused" without providing the information regarding the exact reasons for absence.

Table 1. Summary and comparison of Gilliland, Lewis, and CHIS studies.

Category	Gilliland's School Absence Study (2001)	Lewis' Children Asthma Symptom Study (2013)	Proposed CHIS Study (2023)
Data			
Data source	Children's Health Study (CHS)	Community-based participatory research	California Health Interview Survey (CHIS)
Study year(s)	January 1 through June 30, 1996	11 seasons from Fall 1999- Spring 2002, 14 days each season	2011-2019 for school absence, 2011-2016 asthma symptom
Study areas	12 communities within a 200-mile radius of Los Angeles, CA	2 communities in Detroit, MI (East and Southwest) with predominantly African-American and Hispanic populations were recruited	The whole of California State including all 58 counties
Sample size	2,068 children in the 4th-grade group	298 children (5-12 years) with asthma	10,000+ teens (12-17 years), 7,000+ children (<11 years); about 200,000 adults
Outcome			
School absenteeism			
Related questions	School absence report be completed every 2–4 weeks, follow-up parent interviews for absence reasons within 4 weeks of occurrence	N/A	(1) During the last four school weeks, how many days of school did you miss because of a health problem? (2) Did you attend school last week? (3) During the past 12 months, how many days of school did you miss due to asthma?
Endpoints	Illness-related school absence, respiratory-related absence	N/A	(1) Health-related school absence in the previous 4 weeks (2) School absence (all reasons) in the previous week (3) Asthma-related school absence in the past 12 months
Asthma symptoms			
Related questions	N/A	Asked to self-complete a daily 'checkbox' symptom diary noting the presence or absence of specific asthma symptoms (cough, wheeze, shortness of breath [SOB], chest tightness or heaviness, or waking up at night with asthma symptoms)	"During the past 12 months, how often have you had asthma symptoms such as coughing, wheezing, shortness of breath, chest tightness, or phlegm? Would you say…" The possible answers are 'Not at All', "Less than every Month", "Every Month", "Every Week", and "Every Day".
Endpoints	N/A	Daily asthma symptoms (cough, wheeze, shortness of breath, chest tightness or heaviness, or waking up at night with asthma symptoms)	(1) Having asthma symptoms in the past 12 months (2) Frequency of asthma symptoms in the past 12 months
Exposure Assessment			
Air pollutant	Daily O_3 (1-hr max, 24-hr average, 10 am–6 pm average	Daily O_3 (O_3-8HrPeak, O_3-1HrPeak), only measured in 8 seasons except the first two (Fall 1999 and Winter 2000)	Daily O_3
Exposure window	Not clear, daily?	(1) 1 day prior to the health outcome (lag1); (2) 2 days prior to the health outcome (lag2);	(1) Short-term (1-, 2-, 3-, 4-week average prior to the interview date)

Category	Gilliland's School Absence Study (2001)	Lewis' Children Asthma Symptom Study (2013)	Proposed CHIS Study (2023)
	1-30 lag days, only reported results for 30 lag days	(3) an average exposure 3-5 days before the outcome (lag3-5); (4) an average exposure 1-5 days before the outcome (5DaysAve)	(2) Long-term (3-month, 6 month, 1-year, 2-year, …5-year average etc.)
Assessment method	measured at central-site monitors in each of the 12 communities	measured at 2 community-level monitoring sites established on the rooftops of representative schools in the east and southwest Detroit study areas	O_3 concentrations generated from the chemical transport model (CTM)
Statistical Method			
Outcome variable	Counts: absence count data (% change of incidence rate?)	Dichotomized symptoms (Yes vs. No)	(1) Dichotomized (1: Yes vs. 0: No) (2) Counts (# of school absence days) (3) Ordinary (frequency level of asthma symptoms)
Exposure variable	Continuous	Continuous	Continuous, categorical
Statistical model* (Including sensitivity analyses)	a two-stage time-series model: Poisson log-linear + lag term	Logistic regression	1. Logistic regression; 2. Poisson model; 3. Sensitivity analyses including propensity score weighting method, different exposure lagging time and seasonal variations etc.
Survey weight included*	N/A	N/A	Yes, Final weight + Replicate weight
Covariates adjusted*	Sociodemographic information, day of week, temperature, indoor exposures, medical histories	Demographic information, asthma characteristics, medication use, and presence of environmental tobacco smoke as assessed at the baseline interview	age, sex, race, income/poverty level, race/ethnicity, home smoking exposure, general health status, interview year, interview season, insurance, length of living at current address, rural or urban residential location, housing type, meteorological factors
Strength and Limitation			
Strength	Daily school absence report	Daily symptoms report	1. Including children under 11 and teens 12-17 2. Much larger sample size 3. More recent data from 2011-2019 4. Representative sample of the whole of California 5. O_3 estimates generated from a source-oriented 3D reactive chemical transport model
Limitation	1. 4th-grade children only 2. Smaller sample size (n=2068) 3. 12 communities in South California 4. Limited study period: 6 months in 1996 5. Monitoring-measured O_3 data	1. 5-12 years old children only 2. Small sample size (n=298) 3. East and southwest Detroit study areas 4. Limited study period: 11 seasons 1999-2002 5. Monitoring-measured O_3 data	School absence due to health self-reported in the last 4 weeks

The Contractor will use the CHIS data instead of the Department of Health Care Access and Information (HCAI) data for this proposed study for the following reasons:

1) Despite the popularity of electronic medical records for health care utilization, studies could be done on hospitalizations and emergency room visits such as using HCAI data, however, these data can only reflect the tip of the iceberg of the health issues. Some school absences due to health issues such as headaches or colds may not be serious enough to necessitate urgent medical assistance and thus may not be fully captured in existing medical records but might lead to school absence. As a result, CHIS might serve as a better data source to capture these cases.
2) The number of demographic and socioeconomic variables provided by HCAI data is limited, while besides age, sex, and race/ethnicity, CHIS has also collected various information including income, occupation, full/part-time job status, housing conditions, lifestyle factors (i.e., smoking, physical activity), access to health care, insurance coverage, and co-morbidities, thus providing an opportunity to examine the independent, as well as combined effects of these factors on health outcomes.
3) HCAI data can only link the exposure data at the zip code level, while in CHIS, the exposure level could be assigned based on the respondents' geocoded residential address, thus the geo-linkage quality is high.
4) Last but not least, HCAI data is well-known for the time and labor needed for its application process and data cleaning, it is not realistic to propose using both CHIS and HCAI data. However, HCAI data can be used to study other health endpoints such as ED visits and hospitalizations due to respiratory symptoms.

California Behavioral Risk Factor Surveillance System (BRFSS) data might also be a possible data source, however, BRFSS data are targeted at adults only and include limited questions regarding the asthma prevalence without providing any time information regarding the asthma symptoms. Also, BRFSS data has a small sample (about 2000 adults per year) and has no detailed information on the geolocation of the respondents.

With the recent 9-year data, together with its geo-coded residential address information and interview dates, CHIS is uniquely positioned to study the influence of environmental risk factors on health outcomes such as school absenteeism and asthma symptoms, including air quality across the socioeconomic and geographic diversity of California's population. The Principal Investigator (PI) and others have published extensively using CHIS data.[29-33] Taking advantage of rich CHIS data, the study will focus on both teen and child populations who were school-aged during 2011-2019. For asthma symptoms, the study will assess both short-term and long-term O_3 exposure impacts on adults, teens, and children.

PROJECT TASKS

Task 1. Literature Review

A thorough literature review on research related to the impacts of both short-term and long-term O_3 exposure on a range of adverse health outcomes including but not limited to, school absenteeism, asthma symptoms, and other related health outcomes, especially on vulnerable sub-groups, will be performed. The literature review will provide information on the depth and time frames of previous investigations and will help determine where the previous study is inadequate or outdated for current health impact assessments. The findings will help identify the research gap and the limitations of the existing studies so as to determine the overall scope of the project. Studies conducted in California will be considered the most important and then studies in the United States. Studies conducted outside of the United States will also be included. A summary of the review will be included in the report. The Contractor may also publish a review article.

The list of the specific health endpoints could include:

1) School absence (all reasons, health issue related, specifically asthma-related)
2) Asthma-related symptoms (occurrence [yes vs. no], frequency of the symptoms)
3) Asthma-related emergency room visits and hospitalizations
4) Work loss due to sickness, work loss due to asthma
5) Other respiratory diseases related health endpoints, such as emergency room visits and hospitalizations
6) O_3 effects in subgroups such as race/ethnicity, gender and income.

Task 1 Deliverables: The Contractor will provide CARB a copy of the literature review findings on the impacts of both short-term and long-term O_3 exposure on a range of respiratory health outcomes, including literature on ozone effects such as race/ethnicity, gender and income, tables describing the research according to population, time, exposure and outcome assessment, and main results, as well as manuscripts for publication of these systematic reviews. The literature review findings will be submitted/provided to CARB in Month 6. In addition, this information will be included in the draft final report.

Task 2. Obtain and develop air pollution exposure modeling for O3 exposure measures

The Contractor will obtain the exposure to air pollutants for the study population will be estimated using data from the daily O_3 concentrations generated from the chemical transport model (CTM) developed by Dr, Michael Kleeman from UC Davis -California Institute of Technology (UCD-CIT) with a spatial resolution of 4 kilometers (km), and some selected areas and years are already available at 1-km spatial resolution.
Dr. Kleeman will also provide us with the $PM_{2.5}$ and NO_2 data with the same resolutions. The UCD/CIT airshed model is a reactive 3-D CTM that predicts the evolution of gas and particle phase pollutants in the atmosphere in the presence of emissions, transport, deposition, chemical reaction, and phase change as represented by Equation (1).

$$\frac{\partial C_i}{\partial t} + \nabla \cdot uC_i = \nabla K \nabla C_i + E_i - S_i + R_i^{gas}(C) + R_i^{part}(C) + R_i^{phase}(C) \qquad \textbf{Eq (1)}$$

where C_i is the concentration of gas or particle phase species i at a particular location as a function of time t, u is the wind vector, K is the turbulent eddy diffusivity, E_i is the emissions rate, S_i is the loss rate, R_i^{gas} is the change in concentration due to gas-phase reactions, R_i^{part} is the change in concentration due to particle-phase reactions and R_i^{phase} is the change in concentration due to phase change.[34] Loss rates include both dry and wet deposition. Phase change for inorganic species occurs using a kinetic treatment for gas-particle conversion[35] driven towards the point of thermodynamic equilibrium.[36] Phase change for organic species is also treated as a kinetic process with vapor pressures of semi-volatile organics calculated using the two (2)-product model.[37]

The basic capabilities of the UCD/CIT model are similar to the Community Multiscale Air Quality (CMAQ) model maintained by the U.S. EPA, but the UCD/CIT model has several source apportionment features and more particle size resolution. The UCD/CIT model explicitly tracks the mass and the number concentration of particles in 15 discrete size bins spanning the range from 10 nanometers (nm) through 10 micronmeters (µm), with tracer species used to quantify source contributions to the primary particle mass in each bin. A moving sectional bin approach is used[38] so that particle number and mass can be explicitly conserved with particle diameter acting as the dependent variable. A total of 50 particle-phase chemical species are included in each size bin. Gas-phase concentrations of oxides of nitrogen (NOx), volatile organic compounds (VOCs), oxidants, ozone, and semi-volatile reaction products were predicted using the SAPRC-11 chemical mechanism.[39] Phase change for inorganic species occurs using a kinetic treatment for gas-particle conversion[35] driven towards the point of thermodynamic equilibrium.[36] Phase change for organic species is also treated as a kinetic process with vapor pressures of semi-volatile organics calculated using the 2-product model.[37]

The other potential O_3 estimate source would be the daily O_3 concentrations generated from the CMAQ modeling system at a spatial resolution of 12 km developed by Dr. Joel Wilkins from Howard University.[40] The CMAQ models version 5.0.1–5.3[40-43] used year-specific daily fire emission estimates from SMARTFIRE[44] emissions to simulate changes in air pollution concentrations with and without fires across the United States. Fuel consumption was calculated using the U.S. Forest Service's CONSUME version 3.0 fuel consumption model and the Fuel Characteristic Classification System fuel-loading database in the BlueSky Framework. Wildland fire emissions estimates (which include wildfires, agricultural burns, and prescribed fires) incorporate multiple sources of fire activity, including Earth observations as well as federal, state, local, and tribal databases. Emission factors were taken from the Fire Emission Production Simulator model. Non-fire emissions sources are from the National Emissions Inventory. The model was run with all emissions (fire and non-fire sources) and again without fires.

The daily ambient O_3 estimates generated from CTM or CMAQ models would be assigned to each CHIS respondent by linking the respondents' geocoded home addresses to the surface grid points.

According to the USEPA definition (https://www.epa.gov/iris/iris-glossary) for short-term exposure, which is" repeated exposure by the oral, dermal, or inhalation route for more than 24 hours, up to 30 days", in this study, to investigate the estimated effects of short-term O_3 exposure, the Contractor will use the weekly average concentrations calculated for each respondent for the period prior to the event reported according to the index date (1-week, 2-week, 3-week, or 4-week averages), which has also been done in the previous studies.[29, 45] Similarly, for the long-term O_3 exposure, the yearly average O_3 exposure levels will be calculated for each respondent prior to their index date (1-year, 2-year, 5-year averages) according to what has been done before.[3, 46]

Task 2 Deliverables: Daily surfaces for O_3 exposure levels across the whole of California at a spatial resolution of 4km for years 2011-2019 will be submitted/provided to CARB in Month 12. In addition, this information will be included in the draft final report.

Task 3. Obtain health data from the California Health Interview Survey (CHIS)

This task will comprise the acquisition and coding of health outcomes and exposure measures data for each of the endpoints in the project.
Since 2001, the CHIS, housed at the UCLA Center for Health Policy Research, has been an essential data source to support decision-makers in crafting health policy, as well as planning and funding of California health care and public health programs. Now a continuous survey with an annual target of 20,000 households, CHIS employs a geographically stratified sample design to include households from all California counties. The stratified sample design permits individual county estimates for 41 counties, plus 3 multi-county strata with the 17 smallest counties (by population) combined. During 2011-2019, CHIS was a telephone survey utilizing random digit dial (RDD) sampling methods, with separate RDD samples drawn for landline and cellular telephone numbers. CHIS includes separate questionnaires for adults (age 18+), adolescents (ages 12 to 17), and children (ages 0 to 11), and the survey is conducted in English, Spanish, Chinese Cantonese, Mandarin, Korean, Tagalog, and Vietnamese. The sample sizes of the CHIS child, teen, and adult respondents by race/ethnicity, sex, and county, and age are summarized in the supplemental Table S1&S2.

The Contractor will obtain appropriate approvals for accessing and preparing the three datasets each study year (adult, teen, child) for variable constructions, and data linkage and analyses, including approvals from the Institutional Review Board (IRB) and CHIS Data Access Committee (DAC). The Contractor will develop a data analysis plan and prepare a variable list for review and approval prior to the use of individual-level data. The data plan will describe how the Contractor will avoid inadvertent disclosure of respondents' geographic locations or identities in all working papers, publications, and presentations. The Contractor will use daily O_3 concentrations generated from the CTM developed by Dr, Michael Kleeman from UCD-CIT to develop exposure measures based on CHIS respondents' geo-coded residential addresses. The Contractor will also explore the use of (Community Multiscale Air Quality) CMAQ-modeled O_3 estimates. The details are as follows:

Task 3.1: School-Absenteeism (2011-2019)
<u>For teenagers (12-18 years old)</u>, CHIS asked "During the <u>last four school weeks</u>, how many days of school did you miss because of a health problem?"

Both child (< 12 years old) and teen respondents were asked

1) "Did you attend school last week?" If the respondents selected "No" or "On vacation", then they will be asked, "Did you attend school last year?"
2) "During the past 12 months, how many days of school did you miss due to asthma?"

The Contractor will rely on the information from the questions to construct health outcomes for O_3 exposure examination including:

1) Short-term O_3 exposure impacts on:
   - school absence due to health issues in the last four school weeks (Yes vs. No; and # of school absent days);
   - Not attending school (all reasons without specification of health issues, except for those on vacation or homeschooling) in the last week (Yes vs. No);
2) Long-term O3 exposure impacts on:
   - school absence (all reasons) in the last year (Yes vs. No);
   - the # of school absent days due to asthma in the last year.

Task 3.2: Asthma-related symptoms (2011-2016)
All CHIS respondents were asked about the frequency of asthma symptoms in the past 12 months "During the past 12 months, how often have you had asthma symptoms such as coughing, wheezing, shortness of breath, chest tightness, or phlegm? Would you say…" The possible answers are 'Not at All', "Less than every Month", "Every Month", "Every Week", and "Every Day" between 2011-2016.
The Contractor will examine the frequency of asthma-related symptoms due to O_3 exposure among adults, adolescents, and children as follows:

1) impact of short-term O_3 exposure on frequently having asthma-related symptoms by reconstructing the question information
   - having asthma symptoms (daily, weekly, or monthly vs. No ['Not at All' or "Less than every Month") as a binary outcome variable
   - frequency level of asthma symptoms (1: Not frequently having asthma-related symptoms [including "Not at All' or "Less than every Month"], 2: "Every Month", 3: "Every Week", 4:" Every Day") as an ordinary variable.
2) impact of long-term O3 exposure on
   - having asthma symptoms in the past 12 months (Yes [including "Less than every Month", "Every Month", "Every Week", and "Every Day"] vs. No ['Not at All']) treated as a binary outcome variable
   - frequency level of asthma symptoms (1: "Not at All', 2: "Less than every Month", 3: "Every Month", 4: "Every Week", 5:" Every Day") as an ordinary variable;

Task 3.3 Covariates
The CHIS extensive data collection includes respondent demographics (sex, age, race, ethnicity, height, weight, citizenship status, educational attainment, employment status,

and household income/poverty level), basic health insurance coverage (respondent and spouse/partner), general physical/mental/dental health status, chronic conditions such as diabetes, hypertension and heart disease, basic measures of access to and utilization of health care services (i.e. #of doctor visits, taking medications to control asthma), housing conditions, lifestyle factors (i.e., smoking, physical activity) and length of residence in the neighborhood. These variables will be treated as covariates or confounding factors in the analyses. In addition, the Contractor will also adjust for co-pollutants ($PM_{2.5}$ and NO_2) and the meteorological factors such as hourly "ground-level" temperature used for the CTM calculations from the Weather Research & Forecast (WRF) model, which represents the first 30m of the atmosphere. The meteorological factors generated from gridMET is a dataset of daily high-spatial resolution (~4-km, 1/24th Climatology Lab https://www.climatologylab.org/gridmet.html) will be another source of the data. Temperature would be adjusted as potential confounders, and examine the interaction between temperature and O_3 exposure.

Task 3 Deliverables: Descriptive analysis results for outcome and covariates variables characteristics will be submitted/provided to CARB in Month 12 and Month 15 (for co-pollutants and temperature). In addition, this information will be included in the draft final report.

Task 4. Assess exposure to ambient O3 and health effects (school absenteeism and asthma symptoms occurrence) in children and adults

Task 4.1 Exposure Distribution Analyses

The Contractor will identify different lengths of O_3 exposure windows and characterize the distributions of long-term (1-year, 2-year, 5-year averages) and short-term (1-week, 2-week, 3-week, or 4-week averages) O_3 exposures. Additionally, the Contractor will examine whether the exposures vary by subpopulation, including characteristics such as race/ethnicity, gender, and socio-economic status (SES) as sample size allows.

Task 4.2 Regression Analyses

The Contractor will use standard methods of analysis developed for cross-sectional studies to generate concentration-response curves across increasing exposure units and risk of school absenteeism and asthma symptoms frequency, employing conditional logistic regression or Poisson models to obtain point and interval estimates of odds ratios and relative risks. Methods accounting for exposure lagging time (i.e. 15-30 lag days)[15] and seasonal variations will be applied to explore the effects of O_3 exposures that occurred within certain periods prior to case onset to address concerns that exposures in time periods directly preceding a school absence or asthma symptom frequency may be etiologically relevant. Appropriate modeling approaches will incorporate consideration of possible confounders drawn by formal directed acyclic graph methods (Figure 1), sensitivity analyses, and investigation of the uncertainty in the estimation.

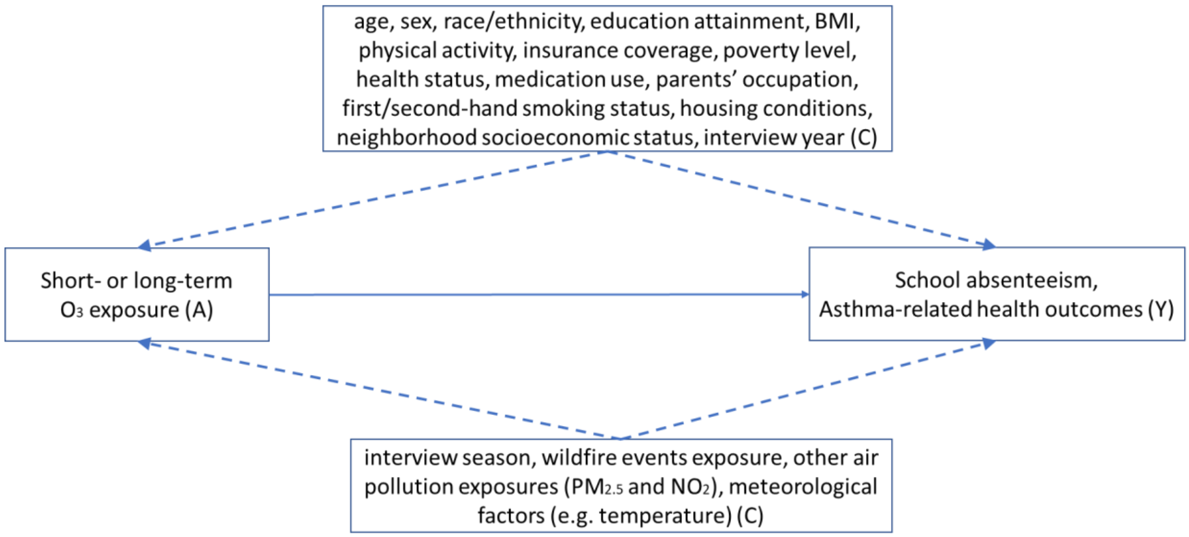

Figure 1. The assumed causal structure of relationships of O_3 exposure (exposure, A) and school absenteeism, asthma-related health outcomes including symptoms onset and related ED visits and hospitalization (outcomes; Y) with measured confounders (C). The confounder variables are collected at individual levels during the CHIS survey. The direct effect is represented by the solid arrow, and confounder pathways are depicted as dashed arrows.

The list of 10 C-R functions to be assessed is listed as follows:

1. School absence (n=6)
    1) short-term O_3 and school loss due to health issues (Yes vs. No) among teens;
    2) short-term O_3 and # of school loss days due to health issues among teens;
    3) short-term O_3 and school absence (all reasons, Yes vs. No) among teens and children;
    4) long-term O_3 and school absence (all reasons, Yes vs. No) among teens and children;
    5) long-term O_3 and school absence due to asthma (Yes vs. No) among teens and children;
    6) long-term O_3 and # of school absence days due to asthma among teens and children;
2. Asthma symptoms (n=4):
    1) short-term O_3 and frequent (every month or more frequently) asthma symptoms (Yes vs. No) using combined adults, teens, and children population;
    2) short-term O_3 and level of frequent asthma symptoms (as an ordinary outcome variable) using combined adults, teens, and children;
    3) long-term O_3 and asthma symptoms (Yes vs. No) using combined adults, teens, and children;
    4) long-term O_3 and frequency of asthma symptoms (as an ordinary outcome variable) using combined adults, teens, and children.

For the types of C-R function, the Contractor would use treat the O_3 exposure as a continuous variable and scaled by its interquartile (per IQR increase), according to the previous literature. If the data allows, then the Contractor can also do dichotomized O_3 exposure (higher vs. lower) using standard cut-off threshold values such as 70 ppb set by the State and National Ambient Air Quality Standards (NAAQS) or 51 ppb set by World Health Organization (WHO), and/or per 10ppb increase in O_3 exposure depending on the data. If data allows, the Contractor can separate into three study groups: adults, teens, and children.

The Contractor will also conduct interaction analyses to identify whether the O_3-related health effects are different by population subgroups such as race/ethnicity, gender, and income groups. Models will also be further stratified to develop the C-R functions by different subgroups including race/ethnicity, SES, and income, if sample size allows, so that to determine differential exposure and health impacts and examine how socioeconomic factors interact with exposures to increase the impact.

In addition, if associations exist, the Contractor will estimate CR functions of school absenteeism and asthma-related symptoms frequency for:

1) different lengths of exposure windows (with different lagging times according to windows of interest before the index date),
2) different O_3 exposure estimates derived from different models.

Task 4.3 Sensitivity Analyses

In sensitivity analyses, besides adjusting for additional covariates such as insurance coverage and meteorological factors, different cut-off thresholds for O_3 exposure levels respectively, as well as alternative exposure window length for short-term or long-term exposure definitions. The Contractor will also co-adjust for daily total $PM_{2.5}$ and NO_2 exposure in the models to address the potential confounding by other air pollutants, as the widely reported health effects of $PM_{2.5}$ and NO_2 exposure. The Contractor will also repeat the analyses using the Firth regression model considering the possibility of small sample bias due to rare events (e.g. few school absence events were reported). The Contractor will also use the Poisson model where robust 95% confidence intervals were estimated by repeating the analysis on 1000 or more bootstrapped samples.

There are some concerns regarding possible measurement errors in the outcome variables due to response bias related to respondents' characteristics, respondents with different ages, genders, races/ethnicities, educations, socioeconomic status, and other characteristics (e.g., health status) might respond differently to the questions; while the Contractor would assume the measurement error for the outcome variable is random, thus, the estimate of the pollution effect on the outcome variable is unbiased. Random measurement errors will be absorbed by the error term in the ordinary least squares (OLS) regression model. However, the larger the measurement error of the outcome, the larger the variance of the estimates and will make inference less precise. To ensure that the assumption of random measurement error of the outcome variable holds (condition on the predictor variables), the Contractor will conduct the doubly robust estimation[47, 48] to improve the covariate balance between the exposed and unexposed cases.

To address the concerns regarding measurement errors in outcome variables due to response bias among people with different socioeconomic statuses, the Contractor will use the propensity score weighting method to mimic an ideal randomized control trial (RCT). In RCT, researchers will randomly assign people to the treatment and control groups and ask about school loss days. Even though the measure of school day loss still has measurement errors, the better-balanced covariates would improve the randomness of the residuals; therefore, assuring an unbiased estimate of the treatment effect of pollution level on the health outcomes. The propensity score model includes all the known confounders including demographic factors such as age, sex, educational attainment, race/ethnicity, and socioeconomic indicators such as household income, as well as lifestyle (i.e., smoking status) and health status. Additionally, because CHIS is a population-based consecutive survey data, both final weights and replicate weight need to be applied in all the analyses to obtain the correct point and variance estimates. The final weight accounts for the sample selection probabilities and adjusts for other known potential sources of bias. The replicate weight is designed for valid variance estimation in the absence of the sample design variables. CHIS used paired Jackknife replicates (JK2), a special case of Jackknife replicate (JKn), to produce the variance of the point estimate. This replication method accounts for all components of the design and the survey weights into the estimates of precision without the need to know such information, limiting biases associated with nonresponse and coverage. Thus, with the weight variables applied, it ensures that estimates represent the California population with the potential variability captured.

The O_3 exposure would be residential address-based, while the Contractor only have the information regarding the school location within limited years (2011-2012), thus the Contractor will do the sensitivity analyses by linking the O_3 surface to school locations within the limited years (CHIS 2011-2012) to assess the association between school-based O_3 exposure and each health outcome. The difference between ambient and personal-level exposure owing to individual behavior such as the use of personal protective equipment would be expected to cause exposure misclassification at the individual level. However, the estimate of ambient O_3 exposure at residences can be considered as the instrumental variable for personal O_3 exposure, that is, personal exposure is the common descendant of ambient exposure and individual behaviors, while individual behaviors are unlikely to influence ambient exposure;[49] therefore, the estimated effects of O_3 exposure on health outcomes are less likely to be affected by confounding from personal behaviors. CHIS asks questions regarding physical activities for the child and teen respondents. In the analyses, the Contractor will also adjust for personal demographics, lifestyle factors (e.g. physical activity), health status, neighborhood SES, and residential location related to personal health behaviors and health. Additionally, CHIS did ask questions about the type of housing. The Contractor will also conduct sensitivity analyses on the type of housing (single house vs. apartments) and/or combined effects with zip code areas on pollutant effects, if the data allows. In addition to adult and adolescent active smoking habits, CHIS also ask if anyone smokes cigarettes, cigars, or pipes anywhere inside the home, and if yes, about how many days per week. Thus, the Contractor will assess exposures to these factors and control for the exposures as potential confounders in the analyses.

Due to potential non-linear associations between air pollution and health outcomes, six different approaches for modeling O_3 concentrations will be considered to examine the O_3 C-R shape for the outcomes, such as linear-threshold, categorical, quadratic, cubic, and cubic spline O_3 C-R models, if the data allows:[50]

1) linear C-R models, in which O_3 concentration was included in the model as a continuous linear variable;
2) linear-threshold C-R models, in which O_3 was modeled as having no effect at concentrations less than or equal to a threshold and a linear effect at concentrations greater than the threshold, where the threshold was determined for outcome by the O_3 level that maximized the log-likelihood of the model;
3) quadratic CR models, in which both linear and quadratic terms for O_3 concentration were included;
4) cubic C-R models, in which linear, quadratic, and cubic terms for O_3 concentration were included;
5) categorical C-R models, in which the effects of quartile- or quintile-based categories of O_3 concentration relative to the lowest quintile of O_3 were determined; and
6) cubic spline C-R models, in which O_3 was modeled as a cubic spline with knot points corresponding to the approximate 25th and 75th percentiles across the O_3 distribution. Cubic spline C-R models included cubic, quadratic, and linear terms for O_3 concentration as well as terms that allowed the cubic term to vary at the knot points.

The Contractor will use the Akaike Information Criteria (AIC) value obtained for each model to compare model fit between models with various O_3 effect specifications, with the lowest AIC representing the best model fit for a given outcome, thus allowing to identify the impacts of O_3 on the individual outcome and to compare exposure concentration-response relationships among overall and subgroup populations.

Sample Size and study power calculation

The study power will differ by outcome and effect size. The Contractor will include over 17,000 children and 9800 teens (>12 years old) plus 180,0000 adults in the study sample (CHIS 2011-2019 pooled with more than 20,000 adult respondents per year). Based on the power calculation for logistic regression with a continuous predictor, to detect an odds ratio (OR) of 1.4 given 2.5 percent of outcome prevalence at the mean of the continuous predictor, the needed sample size is 2,698, with OR 1.2 the needed sample size is 9,187. Since the study will include CHIS data for years 2011-2019 child, teen, and adult respondents, the sample size should be large enough as needed, thus the Contractor expect the sample size to be sufficient to observe similar or even smaller size effects as observed previously, and will also allow the Contractor to conduct subgroup analyses with adequate statistical power.

Table 2. Total sample size required to detect an expected odds ratio at 80% study power and 0.05 alpha level

	Prevalence		
Odds Ratio	2.5%	5%	10%
1.05	128,280	69,415	36,636
1.10	33,616	18,191	9601
1.15	15,634	8,460	4465
1.20	9187	4,971	2624
1.25	6133	3,319	1752
1.30	4437	2,401	1267
1.35	3391	1,835	969
1.40	2698	1,460	771
1.45	2212	1,197	632
1.5	1858	1,006	531

Task 4 Deliverables: Analyses results generated from the models for the relationships between short-term and long-term O_3 exposures and school absenteeism and asthma-related symptoms occurrence will be generated in electronic format through the course of the project and will be submitted/provided to CARB in Month 18. In addition, this information will also be included in the draft final report.

Task 5. Investigate additional health outcomes (asthma-related ED visit and hospitalization, work loss due to sickness) to better understand the health effects related to O3 exposure

Taking advantage of CHIS data, the Contractor will also investigate (1) the impacts of long-term O_3 exposures on asthma-related ED visits and hospitalization among adult, teen and child respondents respectively; and (2) the impacts of both long-term and short-term O_3 exposure on work loss among adult respondents.

<u>For asthma-related ED visit and hospitalization</u>: In CHIS, all adult, teen, and child respondents were asked "During the past 12 months, have you had to visit a hospital emergency room because of asthma?" and "During the past 12 months, were you admitted to the hospital overnight or longer for asthma?" with the answers including: (1) Yes; (2) No; (3) Refused and (4) Don't know.

Thus, the Contractor will use the responses to examine <u>long-term O_3 exposure</u> impacts on:

- asthma-related ED visit in the last 12 months (Yes vs. No);
- asthma-related hospitalization in the last 12 months (Yes vs. No).

Specifically, the two C-R functions for <u>asthma-related ED visits and hospitalization</u> to be assessed are:

1) long-term O_3 and ED visits due to asthma using combined adults, teens, and children population;

2) long-term O_3 and hospitalization due to asthma using combined adults, teens, and children.

Also, the Contractor would treat the O_3 exposure as a continuous variable and scale by its interquartile (per IQR increase) for the types of C-R function. If the data allows, then the Contractor can do dichotomized O_3 exposure (higher vs. lower) using standard cut-off threshold values, and/or per 10ppb increase in O_3 exposure depending on the data. If data allows, the Contractor can separate into three study groups: adults, teens, and child respondents.

For work loss, currently, there are only three studies investigating the relationship between air pollution exposure and work loss, two studies[51, 52] were conducted in the 1980s and one[29] in the 2020s, while none of the three examined the impact of O_3 exposure. Similar to school absenteeism, work loss is usually related to some acute condition exacerbations, such as asthma or hypertension that may not be perceived as serious enough by some people to necessitate medical assistance and thus may not be fully captured in existing emergency room visits, hospital admissions, or mortality data, and may not be fully incorporated into the health-related costs of air pollution exposure, which is critical for informing the policy decisions to public health.

CHIS asked all adult respondents the following questions related to workday loss: “Which of the following were you doing last week?” The answers include: (1) Working at a job or business; (2) With a job or business but not at work; (3) Looking for work; (4) Not working at a job or business. If the respondents chose answers “with a job or business but not at work (answers 2-4),” the respondents were also asked, “What is the main reason you did not work last week?” The answers could be (1) Taking care of house or family; (2) On planned vacation; (3) Couldn't find a job; (4). Going to school/student; (5) Retired; (6) Disabled; (7) Unable to work temporarily; (8) On layoff or strike; (9) On family or maternity leave; (10) Offseason; (11) Sick; and (91) Other. Additionally, CHIS adult respondents were also asked how many workdays they missed because of asthma in the past 12 months.

Thus, the Contractor will use the responses to examine:
1) short-term O_3 exposure impacts on:
   - work loss due to sickness in the last week (Yes vs. No);
2) long-term O3 exposure impacts on:
   - asthma-related work loss in the last 12 months (Yes vs. No and # of work loss days);

The three (3) C-R functions for work loss to be assessed are
1) short-term O_3 and work loss (Yes vs. No) among adults;
2) long-term O_3 and work loss due to asthma (Yes vs. No) among adults;
3) long-term O_3 and # of work loss days due to asthma among adults.

Similarly, the Contractor would use treat the O_3 exposure as a continuous variable and scale by its interquartile (per IQR increase) for the types of C-R function. If the data allows, the Contractor can also do dichotomized O_3 exposure (higher vs. lower) using standard cut-off threshold values, and/or per 10ppb increase in O_3 exposure depending on the data.

Task 5 Deliverables: Analyses results generated from the models for the relationships between short-term and long-term O_3 exposures work loss and asthma-related ED visits and hospitalization will be submitted/provided to CARB in Month 18. In addition, this information will also be included in the draft final report.

Task 6. Delivery of reports, publications, and meeting

The Contractor will provide quarterly progress report and participate in progress update meetings. Three months prior to the end of the study contract, the Contractor will submit a draft final report which will include the results with identified potential health impacts from O_3, sufficiently detailed information on the methodology used, an interpretation of the results, and the certainty of the results. The Contractor will modify the draft report based on the CARB staff review comments. The CARB Research Screening Committee (RSC) will review the modified final report. Once accepted by the RSC, the Contractor will revise the draft report to address any comments of the RSC and any remaining comments by CARB staff. It will also include the preparation of a lay summary of these reports for public dissemination. The Contractor will prepare and provide CARB non-confidential raw data, modeled data, and all data analysis results generated through the course of the project in electronic format. The information from this study can be used to inform the policy-making processes in CARB and can provide additional ways for CARB to demonstrate the potential impacts of CARB's regulations and policies.

In addition, the Contractor will submit a progress report every quarter, using a CARB-designated template and an invoice for the same period if any expenses are incurred during that period. Other deliverables will include analysis results generated through the course of this project, a research seminar in Sacramento at the end of the contract, peer-reviewed publication(s), as appropriate, and additional deliverables to be determined in consultation with CARB staff. The Contractor also plan to disseminate the findings to a broad, targeted, group of individuals and organizations through a webinar. CHPR has its own communications team and a strong track record of success in disseminating research findings to diverse stakeholders across the state.

Task 6 Deliverables: The Contractor will provide CARB including quarterly progress reports and invoices, participation in progress update meetings CARB. Draft and final reports including the preparation of a lay summary of these reports for public dissemination, publications, and PowerPoint slides used for CARB meetings and seminar will be provided. Additionally, all the non-confidential data (e.g. pollutant surfaces) will be delivered at the end of the project. The quarterly report will be submitted/provided to CARB in Month 3, 6, 9, 12, 15, 18, 21, 24. In addition, this information will also be included in the draft final report.

This project will be completed in 24 months from the start date and the detailed tasks and schedule is below.

	MONTHS																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
TASKS																								
1.Literature review	■	■	■	■	■	■																		
2.Prepare Exposure Data	■	■	■	■	■	■	■	■	■	■	■	■												
3.Prepare Health Data		■	■	■	■	■	■	■	■															
3.1 IRB and DAC approval		■	■	■																				
3.2 Outcome variables					■	■	■	■	■	■														
3.3 Covariates					■	■	■	■	■	■	■	■	■	■	■									
4. Data analyses					■	■	■	■	■	■	■	■	■	■	■	■	■	■	■					
4.1 Exposure distribution										■	■	■	■	■	■									
4.2 Descriptive/regression								■	■	■	■	■	■	■	■	■	■	■						
4.3 Sensitivity analyses															■	■	■	■	■					
5. Additional research									■	■	■	■	■	■	■	■	■	■	■					
5.1 Outcome variables									■	■														
5.2 Descriptive/regression										■	■	■	■	■	■	■	■	■						
5.3 Sensitivity analyses															■	■	■	■	■					
6. Report/meetings	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	m		pm			pm			pm			pm			pm			pm			pdm			fm

P = Progress report
D = Deliver draft final report
F = Deliver final report
M = Meeting with CARB staff

Project Management Plan

Our team is composed of well-recognized experts in health policy, air pollution measurement and assessment of human exposure, epidemiology, and medicine. In addition to the research team members mentioned below, the Contractor will also involve staff from CARB.

All project team members will attend bi-weekly meetings to discuss project progress and resolve any questions or issues that have arisen regarding data linkage and analyses. The Co-Investigators will discuss these issues with the PI as needed. The following is a brief description of each team member's background (see details in the attached resumes) and role in the project:

Ying-Ying Meng, Dr.PH, PI, is a co-director of the Chronic Disease Program and Senior Research Scientist at the UCLA Center for Health Policy Research. She has been a principal investigator/program director for many ground-breaking studies to examine a full range of factors affecting health and their complex interrelationships for over 20 years. In her role as the Director of Research at the UCLA Center for Health Policy Research, she has established the Center as a recognized source of important analysis of population-based data (e.g. CHIS and BRFSS) to understand the complex relationship between physical and social environments, and health behaviors. She was the principal investigator for the CARB-granted project titled "Impacts of Short-term PM2.5 Exposure on Work Loss Days". Dr. Meng, as PI, will be responsible for the overall direction and implementation of the project, from design, variable construction, exposure assessment, data linkage, model specification, data analysis, and interpretation, to the production and publication of reports and manuscripts. Dr. Meng will direct all study activities and work with other team members to ensure the successful completion of the study.

Ninez Ponce, Ph.D., Co-PI, is a health services researcher and educator with over 20 years' of experience in policy-relevant research projects that inform the formulation of policies that advance population health and health equity. She is currently the Center's Director as well as Principal Investigator of the CHIS, the nation's largest state health survey, where she leads efforts in measures related to the social determinants of health—race/ethnicity, limited English proficiency, sexual orientation, and gender identity, and immigration/citizenship status. She is a health economist mostly interested in reducing transaction costs levied on consumers and providers that produce racial/ethnic disparities. Her research in multicultural survey research,
social penalties in health and healthcare access, and population-based cancer prevention and control bring relevant content expertise aligned with the CARB's research programs that support CARB's regulatory priorities related to health, environmental justice, economics, air pollution, and climate change.

Michael Jerrett, Ph.D., Co-PI, Professor in the Department of Environmental Health Science, School of Public Health, and Co-Director of the Center for Healthy Climate Solutions, UCLA. Dr. Jerrett is an internationally recognized expert in Geographic Information Science for Exposure Assessment and Spatial Epidemiology, and he was appointed by the U.S. National Academy of Science to the Committee on "Future of Human and Environmental Exposure Science in the 21st Century." Dr. Jerrett is internationally acclaimed for using advanced geographic modeling techniques to estimate short-term and long-term air pollution exposures and for assessing the health effects of exposures including wildfires on a wide range of health outcomes. Dr. Jerrett will work closely with Dr. Meng for the design of the project and will be specifically responsible for the exposure assessment. Dr. Jerrett will also contribute to the publications of the project including manuscripts and reports.

Yu Yu, M.D., Ph.D., Co-I, is a researcher at the UCLA Center for Health Policy Research. Her research focuses on investigating a range of air pollution and noise exposures associated with health outcomes including cardio-pulmonary-metabolic dysfunction and neurodegenerative diseases. Her research also involved examining the health impacts of weather and climate with an emphasis on extreme heat and wildfires. Dr. Yu will provide support to Dr. Meng and other team members in all aspects of project activities. She will be responsible for the daily project activities, including data linkage and analyses, conducting literature searches and synthesizing study findings, drafting summary tables, assisting with the development of presentation materials, manuscripts, and reports to funding agencies, and managing databases, and files.

Michael Kleeman, PhD, professor of the Department of Civil and Environmental Engineering, University of California Davis will serve as a co-investigator and PI for the subcontractor to the project. His research is focused on the study of urban and regional air quality problems with an emphasis on the size and composition of atmospheric particles and gas-to-particle conversion processes.

Meetings

A. Initial meeting. Before work on the contract begins, the Principal Investigator and key personnel will meet with the CARB Contract Project Manager and other staff to discuss the overall plan, details of performing the tasks, the project schedule, items related to personnel or changes in personnel, and any issues that may need to be resolved before work can begin.

B. Progress review meetings. The Principal Investigator and appropriate members of his or her staff will meet with CARB's Contract Project Manager at quarterly intervals to discuss the progress of the project. This meeting may be conducted by phone.

C. Technical Seminar. The Contractor will present the results of the project to CARB staff and a possible webcast at a seminar at CARB facilities in Sacramento or El Monte.

D. Public Webinar. The contractor will organize a plain-language outreach webinar for the public summarizing the results and impact of the project prior to the contract end.

CONFIDENTIAL HEALTH DATA AND PERSONAL INFORMATION (OPTIONAL)

CARB will not be provided access to and will not receive any confidential health data or other confidential personal information under this contract. Further, CARB will have no ownership of confidential health data or other confidential personal information used in connection with this contract. The entities conducting the research in this contract will follow all applicable rules and regulations regarding access to and the use of confidential health data and personal information, including the Health Insurance Portability and Accountability Act (HIPAA) and requirements related to the Institutional Review Board (IRB) process. CARB will not be a listed entity with authorized access to confidential information pursuant to the IRB process for this contract.

HEALTH AND SAFETY

Contractors are required to, at their own expense, comply with all applicable health and safety laws and regulations. Upon notice, Contractors are also required to comply with the state agency's specific health and safety requirements and policies. Contractors agree to include in any subcontract related to performance of this Agreement, a requirement that the subcontractor comply with all applicable health and safety laws and regulations, and upon notice, the state agency's specific health and safety requirements and policies.

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Supplemental Materials:

TableS1. Sample size of California Health Interview Survey (CHIS) respondents 2011-2019.

County	Child 0-11	Teen 12-17	Adult 18-21	Adult 22-60	Adult 61+
ALAMEDA	703	236	200	3085	2388
ALPINE	N/A	N/A	0	15	22
AMADOR	28	10	8	146	227
BUTTE	253	86	109	1127	1112
CALAVERAS	63	26	8	295	492
COLUSA	56	24	22	175	157
CONTRA COSTA	461	156	165	2062	1951
DEL NORTE	37	9	7	149	149
EL DORADO	223	106	66	1042	1124
FRESNO	534	190	187	1771	1446
GLENN	47	27	10	186	250
HUMBOLDT	252	103	75	1186	1164
IMPERIAL	443	195	125	1557	1207
INYO	16	8	6	124	123
KERN	451	167	149	1515	1235
KINGS	402	136	99	1210	971
LAKE	187	74	37	942	1263
LASSEN	31	10	12	147	131
LOS ANGELES	4479	1632	1777	19210	14888
MADERA	356	106	111	1066	1085
MARIN	284	131	90	1290	1765
MARIPOSA	24	8	5	95	118
MENDOCINO	203	69	57	980	1229
MERCED	354	141	134	1144	943
MODOC	13	5	N/A	56	65
MONO	15	3	5	59	49
MONTEREY	305	111	131	1118	976
NAPA	215	95	61	970	1286
NEVADA	189	85	60	918	1273
ORANGE	1227	456	426	5048	4950
PLACER	237	100	82	977	1206
PLUMAS	25	8	7	124	174
RIVERSIDE	1044	379	345	3822	3975
SACRAMENTO	642	221	220	2887	2548
SAN BENITO	292	107	115	1157	951
SAN BERNARDINO	885	332	321	3392	2545
SAN DIEGO	2607	864	832	10039	9276

SAN FRANCISCO	376	109	154	2338	1626
SAN JOAQUIN	309	111	103	1182	993
SAN LUIS OBISPO	209	77	71	909	1246
SAN MATEO	317	112	102	1504	1261
SANTA BARBARA	235	106	125	991	1122
SANTA CLARA	932	302	277	3666	2935
SANTA CRUZ	231	80	97	1075	1041
SHASTA	251	79	51	1057	1191
SIERRA	8	N/A	N/A	20	32
SISKIYOU	86	26	11	372	546
SOLANO	267	75	99	1185	1032
SONOMA	311	118	85	1231	1519
STANISLAUS	317	101	103	1178	1071
SUTTER	335	104	125	1196	1149
TEHAMA	140	43	35	498	595
TRINITY	19	9	4	97	110
TULARE	355	136	113	1156	988
TUOLUMNE	72	27	14	301	487
VENTURA	366	121	124	1409	1425
YOLO	316	116	141	1194	924
YUBA	297	103	86	1146	969

Note. N/A, not applicable.

Table S2. Sample size of California Health Interview Survey (CHIS) respondents by sex and race/ethnicity 2011-2019.

	Child 0-11	Teen 12-17	Adult 18+
Sex			
Male	12047	4303	81458
Female	11287	4070	108296
Race/Ethnicity			
Hispanic	10148	3465	41296
White (NH)	8487	3304	115018
African American (NH)	819	253	9064
American Indian/Alaskan Native (NH)	132	75	1837
Asian only (NH)	2101	738	17718
Native Hawaiian//Pacific Islander (NH)	61	49	419
Two or more races (NH)	1586	489	4402