Impacts of Beijing's coal-to-clean energy policy on local air quality and acute myocardial infarction in adults

Martha Lee

Department of Epidemiology, Biostatistics, and Occupational Health

Faculty of Medicine and Health Sciences

McGill University, Montreal

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Table of Contents

Abstract

Air pollution from household solid fuel burning is a significant source of air pollution and health burden. Nearly half the global population and millions of households in China burn solid fuel as their primary domestic energy source. Policies promoting household transition to cleaner-burning fuels have been implemented in several countries including China, yet few studies have empirically evaluated their real-world impacts. My thesis aims to address knowledge gaps in the understanding of impacts of residential solid fuel use on personal exposures and to evaluate the impacts of a large-scale coal-to-clean energy policy on local outdoor air quality and incidence of cardiovascular disease.

In Objective 1, I obtained over 2000 measurement-days of personal exposure to fine particles ($PM_{2.5}$) and black carbon (BC) in a multi-provincial study of 787 Chinese adults in Beijing, Guangxi, and Shanxi and conducted a series of mixed effects models to investigate within- and between-participant variance components and determinants of exposures. Outdoor $PM_{2.5}$ was the dominant variable explaining within-participant variability in $PM_{2.5}$ (16%). Between-participant variability was partly explained by household fuel use ($PM_{2.5}$: 8%; BC: 10%) and smoking status ($PM_{2.5}$: 27%; BC: 5%). Both indoor sources (solid fuel stoves, tobacco smoking) and outdoor $PM_{2.5}$ were associated with higher exposure. My results indicate that repeated measurements of daily exposure are likely needed to capture longer-term averages, even within a single season, and that measurably reducing exposures in such settings will likely require reductions in emissions from both indoor and outdoor sources, which have different mitigation strategies.

For Objective 2, I used a spatiotemporal model to evaluate association between small area-level exposure to the coal-to-clean energy policy and outdoor $PM_{2.5}$ across Beijing. I obtained satellite-derived ~1x1km $PM_{2.5}$ data from Dec. 2013 to Dec. 2019 (n=17,361 grid cells across Beijing) and developed a geolocated dataset of villages in Beijing that identified villages participating in the policy and the year of entry. Grid cells were defined as exposure to the policy if any villages in the grid cells were participating in the policy. Though regional air quality

in Beijing improved during the study period, I did not find an effect of exposure the policy on local outdoor $PM_{2.5}$, a result which conflicts with previous studies at higher spatial resolution. It is possible that an indoor intervention has limited measurable effects on outdoor $PM_{2.5}$, or that high outdoor $PM_{2.5}$ from other sources combined with my use of spatially-smoothed outdoor $PM_{2.5}$ data limited my ability to capture small local changes in air pollution attributable to a single, source-specific intervention.

In Objective 3 I used a multiple-time point difference-in-difference approach to estimate the effect of the coal-to-clean energy program on acute myocardial infarction (AMI) rates in Beijing townships (n=151). I obtained township AMI incidence for 2013 to 2019 for all adults and separately for sex-age groups. Townships were defined as treated when over 50% of their villages were treated by the policy. Among treated townships there was an average reduction of -5.5% (95% CI: -11.8%, 1.3%) in AMI incidence per 100,000 population in the post-treatment period compared with the pre-treatment period. The largest effects of treatment were among women (-12.1%, 95% CI: -21.2%,-2.0%) and older adults (-12.6%, 95% CI: -20.8%,-3.8%). In men, I only observed effects in the over 65y+ age-group (-9.6%, 95% CI: -17.5%,-1.2%).

My thesis indicates that exposures to air pollution in settings of solid fuel burning are high, variable, and impacted by both indoor and outdoor sources. I observed a cardiovascular benefit in Beijing townships treated by large-scale clean energy policy compared with untreated townships, though I did not observe an effect of exposure to the policy on local air quality.

Abrégé

À l'échelle mondiale, la combustion domestique de combustibles solides est un risque sanitaire courant et important. Cependant, peu de politiques favorisant la transition des ménages vers des combustibles plus propres ont vu leurs impacts évalués. Ma thèse vise à combler les lacunes dans la compréhension des impacts de l'utilisation résidentielle de combustibles solides sur les expositions personnelles et à évaluer les impacts d'une politique à grande échelle de conversion du charbon en énergie propre sur la qualité de l'air extérieur local et l'incidence des maladies cardiovasculaires.

Dans l'Objectif 1, j'ai obtenu plus de 2000 jours de mesure d'exposition personnelle aux particules fines (PM2,5) et au noir de carbone (BC) dans une étude multiprovinciale de 787 adultes chinois. J'ai mené une série de modèles à effets mixtes pour étudier les caractéristiques de la variance entre et dans les participants et les déterminants des expositions.
. Les PM2,5 extérieures étaient la variable dominante expliquant la variabilité intra-participant des PM2,5 (16%). La variabilité entre les participants s'expliquait en partie par l'utilisation domestique de combustible (PM2,5: 8%; BC: 10%) et le statut tabagique (PM2,5 27%; BC: 5%). Mes résultats indiquent que des mesures répétées de l'exposition quotidienne sont probablement nécessaires pour capturer l'exposition à long terme et une réduction mesurable des expositions dans de tels contextes nécessitera probablement des réductions des sources d'émissions intérieures et extérieures.

Pour l'objectif 2, j'ai utilisé un modèle spatio-temporel pour évaluer l'association entre l'exposition au niveau d'une petite zone à la politique d'énergie propre du charbon et les PM2,5 à l'extérieur à Pékin. J'ai obtenu des données satellitaires sur les PM2,5 des cellules de grille d'environ 1x1km de déc. 2013 à déc. 2019. Les cellules de grille ont été définies comme une exposition à la politique si des villages dans les cellules de grille participaient à la politique. Bien que la qualité de l'air régional à Pékin se soit améliorée au cours de la période d'étude, je n'ai pas trouvé d'effet d'exposition à la politique sur les PM2,5 extérieures locales. Il est possible qu'une intervention intérieure ait des effets mesurables limités sur les PM2,5 extérieures, ou

que des PM2,5 extérieures élevées provenant d'autres sources combinées à mon utilisation de données de PM2,5 extérieures lissées dans l'espace aient limité ma capacité à capturer de petits changements locaux dans la pollution d'air attribuée à une seule intervention.

Dans l'Objectif 3, j'ai utilisé une approche de différence dans la différence à plusieurs points dans le temps pour estimer l'effet de la politique d'énergie du charbon vers l'énergie propre sur les taux d'infarctus aigu du myocarde (IAM) dans les cantons de Pékin. J'ai obtenu le taux d'AMI du canton de 2013 à 2019 pour tous les adultes et les groupes d'âge et de sexe séparés. Les cantons ont été définis comme traités lorsque plus de 50 % de leurs villages ont été traités par la politique. Parmi les cantons traités, il y a eu une réduction moyenne de -5,5% (IC à 95%: -11,8%, 1,3%) de l'incidence des IAM pour 100 000 habitants. Les effets les plus importants du traitement ont été observés chez les femmes (-12,1%, IC à 95% : -21,2%, -2,0%) et les personnes âgées (-12,6%, IC à 95% : -20,8%, -3,8%). Chez les hommes, je n'ai observé des effets que dans le groupe d'âge des plus de 65 ans (-9,6%, IC à 95% : -17,5 %, -1,2%).

Ma thèse indique que les expositions à la pollution de l'air dans les environnements de combustion de combustibles solides sont élevées, variables et influencées par des sources intérieures et extérieures. J'ai observé un bénéfice cardiovasculaire dans les cantons de Pékin traités par une politique d'énergie propre à grande échelle par rapport aux cantons non traités, bien que je n'aie pas observé d'effet de l'exposition à la politique sur la qualité de l'air local.

List of Abbreviation

AMI	Acute myocardial infarction
AOD	Aerosol optical depth
ATT	Average treatment effect on the treated
BAM	Beta Attenuation Mass monitor
BC	Black Carbon
BMI	Body mass index
C	Celsius
CAMM	Continuous Aerosol Mass Monitor
CI	Confidence intervals
CIMT	Carotid intima-media thickness
cm	Centimetre
Covid-19	Coronavirus disease 2019
CrInt	Credible intervals
CVD	Cardiovascular disease
DiD	Difference-in-difference
ERA5	European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Version 5
GAINS model	Greenhouse Gas and Air Pollution Interactions and Synergies model
GM	Geometric mean
GMIS	Global man-made impervious surface
GPS	Global positioning system
H-PEM	Harvard Personal Exposure Monitors
HAPIN	The Household Air Pollution Intervention Network
HR	Hazard ratio
ICC	Intraclass correlation coefficient
ICD-10	International Classification of Diseases, Tenth Revision
ICP	INTERMAP China Prospective
INLA	Integrated nested Laplace approximation

INTERMAP	The International Study of Macro-and Micro-Nutrients
IQR	Interquartile range
kgOE	Kilograms of oil equivalent
km	Kilometers
LMIC	Low- and middle-income countries
LPG	Liquefied petroleum gas
lpm	Litres per minutes
MAIAC	Multiangle Implementation of Atmospheric Correction
MI	Myocardial infarction
MICE	Multiple Imputation by Chained Equations
MISR	Multiangle Imaging Spectroradiometer
mm	Millimetres
mmHg	Millimeters of mercury
MODIS	Moderate Resolution Imaging Spectroradiometer
µg	Microgram
NASA	National Aeronautics and Space Administration
$PM_{2.5}$	Fine particular matter
PM_{10}	Coarse particular matter
PTFE	Polytetrafluoroethylen
RH	Relative Humidity
RMSE	Root-mean-square error
RR	Relative Risk
SD	Standard deviation
SDG-7	Sustainable Development Goal 7
SI	Supplementary information
SPDE	Stochastic partial differential equation
TEOM	Tapered element oscillating microbalance
UPAS	Ultrasonic Personal Air Sampler
U.S. EPA	United States Environmental Protection Agency

WAIC	Watanabe–Akaike information criterion
WHO	World Health Organization

List of Figures and Tables

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: Objective 1

Figure S4: Scatterplot of outdoor 24-h average temperature estimated from government monitors using inverse distance weighting versus measured outdoor temperatures in centrally-located clinics in each study village

Figure S5: Pearson correlations between (A) exposures to $PM_{2.5}$ and black carbon (BC) on the same day for all participants and between (B) $PM_{2.5}$ and (C) black carbon exposures on subsequent sampling days for the same participants

Figure S6: Personal exposure to $PM_{2.5}$ by study site and gender in the heating (A) and non-heating (B) seasons

Figure S7. Distributions of average 24-h outdoor $PM_{2.5}$ (estimated from government monitors) in the heating and non-heating seasons at our study sites

Table S1: Personal exposures to $PM_{2.5}$ and black carbon (BC) in peri-urban Chinese adults by socio-demographic and energy use variables (geometric means [95% CI]) in $\mu g/m^3$)

Table S2: Comparison of outdoor $PM_{2.5}$ ($\mu g/m^3$) measured by village monitors and estimated from data provided by nearly government monitoring stations, averaged across study sites

Table S3: Associations between personal $PM_{2.5}$ exposure and selected sociodemographic, energy use, and environmental variables by gender and season, expressed as % change in exposure [95% CI]

Table S4: Sensitivity analysis of associations between personal $PM_{2.5}$ exposure and selected sociodemographic, energy use, and environmental variables, expressed as % change in exposure [95% CI]

Chapter 4: Objective 2

Figure 2: Map of the study area in Beijing showing grid cells where at least one village was exposed to the policy by December 2019

Table 2: Pre-policy air quality, land use, and meteorological characteristics (mean [standard deviation] or n [%]), by exposure group. Grid cells with a village participating in the coal-to-clean energy policy by 2019 are classified as 'exposed' and otherwise as 'unexposed'

Table 3: Effects of area-level (~1x1 km grid cell) exposure to coal-to-clean energy policy, defined as a village in the grid cell participating in the policy, on local satellite-derived $PM_{2.5}$ (µg/m3) in Beijing and 95% credible intervals.

Figure 2: Monthly posterior mean of the latent spatiotemporal effects with exposure defined as having a village in the grid cell participating in the policy during the study period in Beijing

Figure S1: Histogram of proportion of villages in a grid cell exposed to the coal-to-clean energy policy in December 2019. Analysis limited to grid cells with at least one village

Figure S2: Plots of monthly satellite-derived outdoor $PM_{2.5}$ in Beijing during the study period. Data are from the Atmospheric Composition Analysis Group at the University of Washington in St. Louis. White color indicates that $PM_{2.5}$ levels meet China's national standard for maximum annual $PM_{2.5}$ (35 µg/m^3); blue shading indicates areas where monthly average $PM_{2.5}$ is below the annual standard and red indicates grid cells where monthly average $PM_{2.5}$ is higher than the standard

Table S1: Sensitivity analyses of the effects of area-level exposure to the coal-to-clean energy policy on local satellite-derived $PM_{2.5}$ [with 95% credible intervals]

Chapter 5: Objective 3

Figure 1: Study timeline

Figure 2: Township treatment by the coal-to-clean energy policy in Beijing.

Table 1: Township characteristics (median [interquartile range, IQR]) in the pre-treatment period (2013-2014), by treatment group

Figure 3: Overall global weighted average treatment effect on the treated (ATT) per 100,000 population and 95% CI of the coal-to-clean energy policy on incidence of acute myocardial infarction in Beijing townships, by sex and age group. Results from univariate and multivariable multiple time-point models difference-in-difference models

Figure 4: Dynamic aggregate group-time average treatment effect on the treated (ATT) per 100,000 population and 95% CI of the coal-to-clean energy policy on incidence of AMI in

Beijing townships by sex and age-group. Results from multivariable models. Coefficients represent the ATT after 0-2 years of treatment and after 3-4 years of treatment

Table of covariates definitions and sources

Figure S1: Spatial distribution of the proportion of villages and communities in Beijing townships participating in the coal-to-clean energy policy by the end of A) 2017 and B) 2019

Figure S2: Temporal trends in mean and median of log-transformed incidence of acute myocardial infarction (AMI) among adults in eligible Beijing townships from 2007 to 2019

Figure S3: Temporal trends in median age-standardized incidence of acute myocardial infarction (AMI) for Beijing townships by sex and age-group and treatment group for (A) all adults and (B) older adults

Figure S4: Temporal trends in median outdoor temperature and access to health care in eligible Beijing townships. Township averages are presented for the pre- and post-treatment periods and by treatment group. Townships were considered treated when more than 50% of village and communities in the township were participating in the coal-to-clean energy program in that year

Table S1: Township characteristics (mean and standard deviation) in the pre-treatment period (2013-2014), by treatment group

Figure S5: Histograms of all 6000 lower 95% CI estimates of average treatment effect on the treated (ATT) per 100,000 population generated from the 6000 runs of the multiple time point different-in-difference used to generate the confidence intervals for the main analysis

Figure S6: Histograms of all 6000 upper 95% CI estimates of average treatment effect on the treated (ATT) per 100,000 population generated from the 6000 runs of the multiple time point different-in-difference used to generate the confidence intervals for the main analysis

Table S2: Average treatment effect on the treated (ATT) of the clean energy program on acute myocardial infarction (AMI) incidence (events per 100,000) in Beijing townships [with 95% confidence intervals]: results from a staggered difference-in-difference analysis adjusted for covariates

Chapter 6: Discussion

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Contribution to Original Knowledge

Objective 1: This objective focused on the measurement and modeling of personal exposure to $PM_{2.5}$ and black carbon in a multiprovincial study of older Chinese adults. The goal was to understand the determinants of both variability and levels of exposure. This is one of very few studies to conduct repeated daily measures of exposure to $PM_{2.5}$ and black carbon in settings of household solid fuel burning. The study is unique in its inclusion of both men and women and of exclusive clean fuel users living in the same communities as solid fuel users. It informs exposure assessment strategies for future epidemiologic and intervention studies and facilitates for more realistic estimation of the potential air quality and health benefits of clean energy interventions in future risk assessments.

Objective 2: Household energy use is an important contributor to air pollution and adverse health outcomes in Beijing. This objective evaluates the association between changes in local outdoor satellite derived $PM_{2.5}$ and exposure to the coal-to-clean-energy policy in Beijing. This policy is one of the largest clean energy policies to date, but evaluation of its impacts on air quality are limited to risk assessments, small cross-sectional field studies, or empirical assessments conducted at large spatial scales (e.g., districts or municipalities). My prospective study is the first to empirically assess the air quality impacts of the coal-to-clean energy policy for all of Beijing at a local-level (~1km×1km) and my analytical approach is unique in capturing the complex spatial and temporal correlation through the inclusion of a latent (unobservable) structure. This approach prevents a bias structure within the residuals and incorrect accounting of uncertainty of the point estimates, which is an important methodological strength compared with previous studies evaluating the air quality impacts of household energy policies.

Objective 3: Cardiovascular disease is the leading cause of death in China, and identifying population interventions to reduce cardiovascular disease burden is a national priority. This objective examines the impact of the coal-to-clean-energy policy on township incidence of acute myocardial infarction (AMI) in all adults and for different age-sex demographic groups using a pre-post policy design with a control (untreated) group. This is the first study to empirically assess the health effects of the coal-to-clean energy policy and one of very few studies globally to evaluate the population health impacts of a clean energy policy.

Contribution of Authors

Objective 1: Martha Lee, Ellison Carter, Li Yan, Queenie Chan, Paul Elliott, Majid Ezzati, Frank Kelly, James J Schauer, Yangfeng Wu, Xudong Yang, Liancheng Zhao, Jill Baumgartner
ML processed the black carbon data, performed the statistical analysis, and wrote the manuscript. Laboratory analyses of $PM_{2.5}$ and black carbon were conducted at the Wisconsin State Hygiene Laboratory, and the $PM_{2.5}$ data were processed by EC. JB designed the study with ME and XY and supervised the statistical analysis and writing of the manuscript. EC, LY, LZ, and JB organized and supervised data collection. All authors provided input on the study design, measurements, and data analysis and provided feedback on the manuscript and revisions. All authors approved the final version of the manuscript.

Objective 2: Martha Lee, Alexandra Schmidt, Guofeng Shen, Shu Tao, Jill Baumgartner
ML collated and processed the data for this secondary data analysis, performed the statistical analysis, and wrote the manuscript. ML, ST, AS and JB designed the study and supervised the statistical analysis. ST provided the panel data on exposure to the coal-to-clean energy policy. All authors provided input on the study design and data analysis and provided comments and feedback on the manuscript.

Objective 3: Martha Lee, Jie Chang, Shu Tao, Guofeng Shen, Sam Harper, Jill Baumgartner, Jing Liu
ML and JC contributed equally to this manuscript and therefore share first authorship. ML, JC, JB and JL co-designed the study, with input from GS and ST. ML collated and processed township-level data on treatment by the policy and relevant covariates and developed the initial statistical code for analysis. JC generated the age-and sex-specific township-level estimates of incidence of acute myocardial infarction (AMI) and ran the statistical models in China using the code written by ML. ST provided the panel data on exposure to the coal-to-clean energy policy. SH contributed to the statistical analysis including suggestions for sensitivity analyses. ML and JC drafted the manuscript, with input from JB and JL who co-supervised the study. All authors provided feedback on the manuscript.

Chapter 1: Introduction

1.1 Preface

My thesis focuses on household energy use and energy transition and their impacts on air pollution exposures and cardiovascular disease in China. My first objective focuses on measurement and modeling of personal exposure to air pollution ($PM_{2.5}$ and black carbon) among adults enrolled into the INTERMAP China Prospective study. These detailed air pollution exposure data were collected by local research staff as part of the larger INTERMAP China Prospective study which also conducted measurements of subclinical cardiovascular outcomes and other variables in 2015-2016. Follow-up measurements were planned for 2020-2021 and were intended to form the basis for my last two thesis objectives. However, due to travel restrictions during the COVID-19 pandemic, data collection planned for 2020-2021 was suspended and I shifted my original thesis aims. The second and third objectives still focus on household energy use and its air pollution and health impacts but use existing satellite-derived air quality data and administrative data on acute myocardial infarction (AMI) data from China that did not require primary data collection (Objectives 2 and 3). The overall focus of my thesis on household energy use and its air pollution and cardiovascular impacts remained the same, however the data and questions shifted to accommodate the travel and field data collection restrictions during the pandemic.

1.2 Thesis Outline

This thesis contains six chapters. The first chapter introduces my research objectives and the key knowledge gaps that my thesis aims to address. Chapter 2 provides a review of the literature that motivated this thesis. It focuses on the magnitude of exposure to air pollution in settings of household solid fuel use both globally and in China, the burden of disease from cardiovascular outcomes and air pollution exposure, previous household energy policies, and the air quality polices in Beijing. Chapters 3-5 describe the research conducted for each of the three individual objectives in my thesis. Chapter 6 contains the concluding statements about the outputs of my research and includes a synthesis of the overall research findings, the strengths and limitations of this work, and a proposal for future research to move this work forward.

1.3 Knowledge Gaps

Air pollution is a ubiquitous environmental exposure that is emitted from range of indoor and outdoor sources, including motor vehicles, industry, and tobacco smoking. Residential solid fuel burning for heating and cooking is another important source of household (indoor) and outdoor air pollution, especially in low- and middle-income countries (LMICs) (1). Over 3.8 billon people globally and 508 million people in China (36% of the population) primarily burn solid fuel for cooking, heating, lighting or other household tasks (1). The practice is most common among populations living in rural and peri-urban areas where wood fuel is more commonly available and thus easily harvested, though it persists in many urban communities in LMICs. Most households burn solid fuel in rudimentary stoves (e.g., three-stone fires) that are inefficient and emit high levels of air pollution into homes and communities. Emissions from solid fuel (e.g., crop residues, wood, raw coal, and coal briquettes) are 4-25 times higher than those from liquefied petroleum gas (LPG) (2).

Incomplete combustion of solid fuel emits many health-damaging air pollutants, including carbon monoxide, nitrogen oxides, and fine particles less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$). $PM_{2.5}$ is microscopic in size and is the air pollutant most strongly associated with a range of health impacts (1, 3). Thus $PM_{2.5}$ is a commonly regulated and monitored air pollutant globally (4). Use of solid fuel stoves and the resulting exposure to $PM_{2.5}$ is recognized as being associated with a number of adverse health outcomes in adults and children, including cardio-respiratory diseases and early mortality, poor maternal and birth outcomes, and neurocognitive impacts (1, 5, 6), and contribute to a substantial portion (35%) of the estimated global burden of disease attributable to air pollution (1, 6). However, several key knowledge gaps limit epidemiologic studies and intervention evaluation to inform policy.

First, despite household solid fuel being among the most prevalent environmental exposures, there are relatively few studies with field data on personal exposure to $PM_{2.5}$ in such settings (7), and even fewer with multiple days of measurement (8-12) or that assess exposure among men (11, 13, 14). Measurements of $PM_{2.5}$ exposures in exclusive clean fuel users relative to users of solid fuel in the same setting are also rare (7, 14). Estimating the health burden of household air pollution and the potential benefits of a transitioning from solid fuel stoves to clean fuel requires a realistic understanding of the levels and source contributors to personal exposures.

Second, there is limited evidence on the air quality and health benefits of household energy interventions and policies aimed at reducing household solid fuel use through the promotion of clean fuels like gas or electricity. Smaller-scale randomized trials of cookstove interventions found that other air pollution sources like industry, road traffic, or neighbor's solid fuel use can mask the air quality benefits of a household stove intervention with air pollutant levels remaining well above World Health Organization's (WHO) health-based guideline (15, 16). Though a number of countries are implementing national or regional household energy interventions or policies, impact evaluations of the effects are rare because it can be difficult to match the timelines for evaluation with that of intervention implementation and because it is challenging to account for background trends in health and air pollution levels (17).

My thesis directly fills these knowledge gaps by 1) providing new information on the relative contribution of indoor versus outdoor sources on personal air pollution exposures in a complex air pollution setting where household solid fuel use is common; and by 2) evaluating the impacts of a large-scale clean residential energy policy on air quality and cardiovascular outcomes in Beijing.

1.4 Research Objectives

My thesis investigates the indoor and outdoor source contributors to personal exposures in settings of household solid fuel use and leverages the stepped implementation of the Beijing coal-to-clean energy policy to estimate its impacts, with the following objectives:

Objective 1: Estimate the within- and between-participant variance components and source determinants of personal exposure to $PM_{2.5}$ and black carbon in a multiprovincial study of Chinese adults using solid fuel stoves.

I used field-collected data to conduct a panel study with up to four days of repeated measures of 'gold standard' measurement of personal exposure to $PM_{2.5}$ and black carbon in 787 men and women (ages 40–79) living in rural and peri-urban villages in northern (Beijing and Shanxi) and southern (Guangxi) China. Outdoor $PM_{2.5}$ and questionnaire data on sociodemographic characteristics and indoor pollution sources including tobacco smoking and solid fuel stove use were simultaneously collected. The resulting over 2000 days of personal exposure measurements were used in a series of linear mixed effect models to estimate the within- and between-individual variability in exposure and to identify the determinants of both variability and levels of exposure.

Objective 2: Estimate whether exposure to the coal-to-clean-energy program is associated with changes in outdoor satellite-derived $PM_{2.5}$ in Beijing.

I obtained satellite-derived air pollution data for heating season months between December 2014 to December 2019 at the small area level (~1x1km grid cells) for Beijing. To estimate area exposure the coal-to-clean energy policy, I developed a geolocated dataset of all villages in Beijing that included information on whether the village participated in the policy and year of entry. I then used a spatiotemporal model to estimate whether exposure to the policy, defined as having a village in the grid cell exposed to the policy, was associated with changes in satellite-derived $PM_{2.5}$ after adjusting for covariates.

Objective 3: Assess the effect of treatment by the coal-to-clean-energy program on incidence of acute myocardial infarction (AMI) in Beijing townships.

I leveraged township data from Beijing on acute myocardial infarction and participation in the coal-to-clean energy policy from 2013 to 2019 and conducted a multiple time point difference-in-difference analyses to assess whether treatment by the policy, defined as having more than 50% of villages in the township treated, affected incidence of AMI for all adults and separately for different sex and age groups. The analyses included multiple treatment periods, allowing me to assess the cardiovascular effects of the policy for townships treated longer versus shorter.

Chapter 2: Literature Review

In this section I will review literature that is relevant to the objectives of this thesis: air pollution (outdoor and household), household solid fuel use, acute myocardial infarction (AMI), and the interventions and policies aimed at mitigating and reducing exposure to air pollution. I review the global and China-specific literature in these areas as they pertain to this thesis.

2.1 Air Pollution

Air pollution is a ubiquitous environmental exposure that varies spatially and temporally and is causally associated with a number of adverse health outcomes, including the development of cardiovascular disease (1). The objectives in my thesis stem from this understanding with air pollution being central in each of the three objectives.

Air pollution is any air contaminate of the indoor (household) or outdoor environment by a chemical, physical or biological agent that modifies the natural characteristics of the atmosphere (4). This broad definition of air pollution encompasses many gaseous and particulate pollutants including ozone, carbon monoxide, sulfur dioxide, nitrous oxides, volatile organic compounds, methane, particulates, and pollen. Air pollution comes from both anthropogenic (e.g., solid fuel burning, industry emissions) and natural sources (e.g., dust, sea salt, volcanic eruptions, wildfires). Though the particulate matter emissions from different combustion sources share many of the same chemical components, the overall chemical composition varies by fuel type and combustion efficiency. Due to the vast number of pollutants, generally single or a few pollutants are used to define overall air quality and estimate the health risks posed by air pollution. An air pollutant of high importance to human health is fine particulate matter less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$), which is widely monitored and regulated because it is the pollutant size most strongly associated with adverse health outcomes (4, 18, 19). Within this thesis, I thus focus on $PM_{2.5}$ and its household (indoor) and outdoor sources as they determine personal exposure in settings of household biomass and coal burning.

2.1.1 $PM_{2.5}$ and black carbon

Fine particles ($PM_{2.5}$) are emitted from a range of sources including industry, motor vehicles, agriculture, household solid fuel burning, and forest fires. They persist in the atmosphere and can be transported long distances because of their smaller size. $PM_{2.5}$ has an atmospheric half-life of days to weeks compared with the minutes or days for coarse particulates (2.5 to 10 microns in aerodynamic diameter) (20). By persisting in the atmosphere for longer, they can pose a health hazard far downwind and weeks after their emission into the environment in addition to their immediate source region.

Measurement of $PM_{2.5}$ is typically represented as a mass-based concentration, specifically micrograms (μg) of particles per cubic meter (m^3) of air. Particles are emitted from a range of combustion (transportation, industry, wildfires, solid fuel combustion) and non-combustion sources (e.g., dust, sea salt) (21, 22). Incomplete combustion occurs when there is insufficient oxygen supplied to a combustion reaction. Instead of the complete production of only CO_2 and water, particulate matter and gases are also released.

The total mass of $PM_{2.5}$ comprises different chemical components including sulfates, nitrates, ammonium, elemental and organic aerosols, metals, and salts. The chemical composition of $PM_{2.5}$ varies depending on several factors including the emissions source, combustion conditions, meteorology, and time in the environment (23-25). Due to their small size, $PM_{2.5}$ can penetrate deep into the lungs (into the secondary bronchial area passage) and into the bloodstream (26, 27). They have been shown to affect multiple organ systems and impact health across the life course. For these reasons, $PM_{2.5}$ is the pollutant most commonly monitored by countries and the World Health Organization (WHO) for air quality standards and guidelines (4, 28).

Black carbon is the soot component of $PM_{2.5}$ and a more specific pollutant marker of emissions from incomplete combustion of sources such as fossil fuel, wood, coal, and other fuels (29). Black carbon and elemental carbon are operationally defined by their measurement method (e.g., optical versus chemical measurement, respectively), although the terms are often used interchangeably because they are both measuring light-absorbing particles (29). Previous studies of outdoor (ambient) and household air pollution indicate that combustion-related air pollution, when measured by black or elemental carbon, may be more strongly associated with adverse cardiovascular impacts of air pollution than the total mass of $PM_{2.5}$ (30, 31).

2.1.2 Sources of air pollution

A common distinction when studying air pollution is to divide its sources into categories of outdoor and household/indoor. This distinction is largely because the mitigation strategies for indoor versus outdoor sources differ considerably, even though the two influence each other through indoor-outdoor air exchange of air (32). Outdoor sources of air pollution including transportation, industry, and agricultural burning have generally been better studied (33-35). Household/indoor sources, particularly of particulate matter, include tobacco smoking and household use of solid fuel stoves for cooking and heating. Surveys conducted in Canada (36), China (37), Germany (38), and the United States (U.S.) (39) indicate that people spend an average of 80-90% of their time indoors which makes the indoor environment an important source of exposure, potentially more relevant than outdoor (1, 40). Due to lower volumes of air for dispersal and the close proximity to sources, the indoor concentrations of pollutants can be much higher than outdoors (41). Understanding the sources of air pollution also allows for targeted interventions aimed at reducing air pollution emissions and population exposures.

2.2 Measuring and Modelling Exposure to $PM_{2.5}$

2.2.1 Technologies for measuring exposure to $PM_{2.5}$

Integrated gravimetric measurement of $PM_{2.5}$

The gold standard for measurement of $PM_{2.5}$ is gravimetric sampling where air is pulled through a filter at a known and carefully regulated flow rate. The flow paths and flow rates of the gravimetric samplers are designed to capture particulate matter greater than 2.5 microns in aerodynamic diameter before they reach the filter so that only $PM_{2.5}$ is sampled (42). The filters are weighed in a temperature and humidity-controlled environment before and after sampling, and the change in weight is then divided by the volume of air sampled. This concentration represents the integrated (average) mass of $PM_{2.5}$ during the entire sampling period, after subtracting for a blank filter (control) concentration.

Gravimetric measurements are typically integrated over daily, monthly, or annual time periods to estimate 'usual concentration' for exposure, epidemiology, and intervention studies and for comparison with the WHO or country-specific standards and guidelines (43, 44). The gravimetric method is non-destructive such that the filter-based samples can be further analysed for their optical and chemical composition, which provides information on the relative contribution of different sources to the total mass of $PM_{2.5}$.

There are several limitations of gravimetric $PM_{2.5}$ sampling for large-scale epidemiologic studies, especially in LMICs where population exposure to air pollution is generally understudied compared with Europe, North America, and urban China (42, 44-46). First, integrated gravimetric assessment provides the average $PM_{2.5}$ mass concentration for the sampling period but does not provide temporal information like periods of high concentrations. This information can be used to identify activities associated with higher concentrations, for example changes during commuting times or during certain types of household energy events. Second, gravimetric instruments tend to be bulky, expensive, have limited battery life, and their operation requires trained staff and frequent maintenance. Scaling up these measurements to achieve a large sample size is resource-intensive and wearing the monitors is burdensome to participants, especially for high-risk populations like infants and children, pregnant women, and the elderly. Further, the laboratory measurement of mass requires a very accurate and sensitive microbalance that is housed in a climate-controlled setting which are rare in many places in the world (47). Finally, in high pollution settings, the measurement itself can be challenging because the filters can overload (i.e., accumulate so much mass that the flow rate is affected or the sampler stops working), which affects the accuracy and comparability of the measurement.

Alternatives to integrated gravimetric measurement of $PM_{2.5}$

Several reference-grade technologies offer advantages over the more labour-intensive manual gravimetric methods in terms of their measurement time resolution and operating costs, but they are still very expensive and lack portability. Continuous Aerosol Mass Monitors (CAMMs) or Tapered Element Oscillating Microbalance (TEOMs) are commonly used monitors that apply gravimetric principles to measure real-time $PM_{2.5.}$ CAMMs compare pressure differences between air channels containing a filter with sampled $PM_{2.5}$ and a reference channel that contains a clean filter and TEOMs measure changes in the oscillation frequency of tapered oscillating glass rod on which the sampled $PM_{2.5}$ is deposited (48, 49).

Another commonly used measurement approach is the optical measurement of particles which, like gravimetric sampling, uses a pump to pull air through the monitor but estimates mass using optical characteristics. Two commonly used optical methods are light scattering or beta-attenuation (50, 51). Light scattering sensors measure light (generally infrared or red light) scattered by the particles as they pass through the sensors using assumptions of particle shape and refractive index (51). Beta-attenuation monitors (BAMs), one of the most widely used reference monitors (48, 52), measure the reduction in beta-ray intensity after passing through a medium that collect the $PM_{2.5}$. Built-in reference conversion factors convert these optical measures to estimated $PM_{2.5}$ mass (48). The outputs still need to be empirically calibrated against a reference gravimeter sampler or a very high-cost reference grade optical sensor because $PM_{2.5}$ varies in its chemical composition over time and space so the reference conversion factor varies.

Though not a focus of this thesis, it is important to note that the enormous development of low-cost optical sensors in the last decade. These sensors provide less accurate measurement than the reference quality monitors described above, especially at very low and very high concentrations, but are a less expensive option for providing time-real measurements of $PM_{2.5}$ at a larger number of locations (53, 54). Most low-cost sensors use light scattering technology to estimate $PM_{2.5}$ mass (50, 51). These sensors enable spatially dense, high temporal resolution measurements of air quality that would be logistically infeasible and cost-prohibitive with traditional reference monitors. Low-cost PM sensors are especially beneficial for achieving great spatial and temporal resolution of air pollution measurements in LMIC settings where few, if any, reference grade measurements exist and in areas where air pollutants have large spatial gradients.

Aerosol Optical Depth (AOD) measurements are also used to estimate outdoor ground level $PM_{2.5}$ measurements through modelling or semi-empirical approaches. Like optical sensors, these measurements are most accurate when corrected using ground-level $PM_{2.5}$ monitors (55). Meteorological variables and chemical transport/dispersion modelling can also be integrated to increase accuracy (55, 56). The AOD is a quantitative measure of the extinction of a ray of light as it passes through the atmosphere. It is used as a surrogate measure of $PM_{2.5}$ since the extinction of light results from particulate matter in the atmosphere. AOD can be retrieved from various satellites, e.g., the Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua satellites. While this surrogate measurement facilitates much greater temporal and spatial coverage and resolution than traditional methods of air quality measurement, satellite-derived $PM_{2.5}$ estimates are less accurate than field measurements for ambient air pollution and they are less able to capture the contribution of local sources to outdoor $PM_{2.5}$ (57).

2.2.2 Scale of measurement

Air samplers (e.g. gravimetric or optical) can be used to gather personal (e.g., portable samplers in attached to an individual), household (indoor), or outdoor/ambient air pollution measurements (e.g., samplers placed in homes or at community sites). Outdoor regulatory monitors are limited in their spatial resolution since they are stationary and can only provide discrete measurement at locations where the samplers are placed. To provide better spatial coverage, some studies implement dense networks of air monitors and sensors or mobile monitoring (generally sensors installed on vehicles), though these are largely limited to urban settings and do not directly capture indoor sources, which, in settings of household solid fuel burning, are a major contributor to human exposures and the primary focus of clean energy intervention. Long-term outdoor pollution monitoring typically requires substantial upfront and ongoing investment in technology, operation and maintenance, and staff, and are typically operated by government agencies or universities.

Household (indoor) measurements are stationary measurements collected inside homes, generally in the kitchen, bedroom, or living areas where occupants tend to spend the most time. They better capture indoor sources like solid fuel emissions, environmental tobacco smoke, or incense burning, but like outdoor monitors they might not capture the full profile of air pollution exposures since people move between the indoor and outdoor environments. Long-term measurements of indoor air pollution are uncommon due to participant burden and power requirements, though recent improvements in battery technology and electrification in households in LMICs has facilitated longer-term measurements in more recent studies (44).

Direct personal exposure measurement using portable instruments provides a more accurate measure of human exposure, but the samplers are still bulky, burdensome for participants, and have limited battery life which limits long-term measurements beyond 1-3 days. This limits their usefulness for epidemiologic and intervention studies which are most interested in long-term ('usual') exposure measurements that are most relevant to health (1, 4, 58). In Chapter 3 of this thesis, I report on a study that measured personal exposure to $PM_{2.5}$ for 787 participants for up to 4 days in two seasons, which is still only a snapshot for a time-varying exposure like air pollution but is still one of the largest and most comprehensive personal exposure studies conducted in a setting of household solid fuel burning.

2.2.3 Methods for assigning $PM_{2.5}$ exposure

To estimate population exposures to $PM_{2.5}$ at high spatial and temporal resolution, many studies generate continuous outdoor $PM_{2.5}$ exposure surfaces at high spatial and/or temporal resolution through various statistical or other modeling approaches, including land-use regression modelling, satellite AOD, or a combination of multiple approaches, and assign these estimated values to study participants (59, 60). The simplest methods involve assigning air pollution exposures based on the concentrations recorded by the nearest stationary outdoor monitor (59). Regression models using spatial predictors trained on dense networks of ground level $PM_{2.5}$ monitors are more computationally complex but are a commonly used population-based exposure assessment tool for epidemiologic studies where participants' exposures are assigned based on residential location (59, 60). These continuous surfaces can also utilize satellite AOD data or data collected through mobile monitoring. Satellite-derived $PM_{2.5}$ is the most commonly used data source for estimating population exposures to air pollution for LMICs, for which spatially-resolved measurements of air pollution data are lacking (55, 61).

In most urban settings, estimates of outdoor $PM_{2.5}$, generated through these indirect methods are assigned as the exposure to pollution based on an individual's city of residence, postal code, or home address. These group-level averages are logistically much easier than personal exposure assessment, but do not fully capture the between-individual variability in exposures that are driven by local and indoor sources and human behaviors (62). In settings of residential solid fuel burning, where indoor sources contribute substantially to personal exposure, measurement of outdoor $PM_{2.5}$ does not accurately capture the differences in exposure between individual attributable to solid fuel burning. For example, in a recent systematic review of 140 personal exposure studies conducted in 40 countries, Lim et al. (2022) found that personal exposures to $PM_{2.5}$ tended to be only slightly higher than outdoor $PM_{2.5}$ in urban settings but where much higher in rural areas in LMICs (44). In rural areas in low-and low-middle-income countries the ratio of personal exposure to ambient exposure was 1.5 (44). In upper-middle-income countries including China, this ratio was 5.1, meaning the use of ambient concentrations as a proxy for personal exposure would significantly underestimate actual exposure (44).

2.3 Global Air Pollution Exposure

The majority of the world's population (~99%) lives in places where outdoor air pollution is estimated to exceed the WHO annual guideline for $PM_{2.5}$ of 5 μg/m^3 (63). The guideline was lowered from 10 to 5 μg/m^3 in 2021 due to convincing evidence of health effects at low exposures (64). Air pollution is a global concern but its risk it not equally distributed. Populations in LMICs face the greatest risk of exposure as outdoor air pollution is high and household solid fuel use contributes to high levels of household air pollution (1). Concentrations in cities in LMICs are on average 17 times higher than cities in the USA, Canada, and Europe (65). In 2019, for example, Beijing was estimated to have city-wide average annual population-weighted $PM_{2.5}$ of 55 μg/m^3, while Montreal was estimated to have an average of 9 μg/m^3 (35).

Use of solid fuels is higher in LMICs and particularly common in sub-Saharan Africa and parts of Asia (1). While less than 1% of Canada's population primarily uses solid fuel for cooking, nearly the entire population of the Central African Republic cooks with solid fuel (1). Household solid fuel burning is a major source of air pollution exposure. A systematic review of studies conducted from LMICs (43), found daily average $PM_{2.5}$ personal exposure ranged from 40 to 186 μg/m^3 in settings of household solid fuel burning (65), which is considerably higher than the WHO's ambient guidelines of 5 μg/m^3 (annual) and 15 μg/m^3 (24-hour) (4). Transitioning to cleaner burning fuels or stove technologies has been the focus of a number of initiatives to improve air quality and population health (66).

2.3.1 Air pollution exposure from household solid fuel burning

The use of solid fuels (e.g., coal, biomass, and dung) for cooking, heating, and other domestic tasks (e.g., water boiling, lighting) is a common source of global exposure to air pollution. An estimated 3.8 billion people burn solid fuel as their primary cooking fuel (1). Use of solid fuel is more prevalent in LMICs as these fuels are generally inexpensive or free, except for harvesting costs, and can be more readily available compared with electricity and gas which have higher cost and require a certain level of infrastructure for delivery (1, 67). This infrastructure is not consistently available in many resource-poor settings .There also can be traditional and cultural values attached to using traditional stoves and fuels which can further disincentivize transition to higher-cost clean fuel (67, 68).

The proportion of the world's population primarily using solid fuel for cooking has decreased from 53% to 36% between 1990 and 2020, driven largely by shifts in China and India where aggressive clean energy policies were implemented and where large segments of their populations moved into cities (1). Yet the absolute number of solid fuel users has remained relatively consistent due to population growth, particularly in low-income countries and rural areas of middle -income countries (1, 69). Thus, it is anticipated that household use of solid fuel will persist for many decades in the absence of major shifts in clean energy.

Solid fuels are typically burned in open fires or rudimentary stoves with low energy efficiency, resulting in incomplete combustion and high emissions of air pollution into homes, communities, and the environment (70, 71). Household coal stoves have higher particle-phase emissions than coal burned in the industrial and power sectors. This is due to less efficient combustion and a lack of after-treatment controls, which has resulted in residential stove emission factors that are two orders of magnitude higher than industrial burners (70). A large multi-country study of household $PM_{2.5}$ in 2541 households in Bangladesh, Chile, China, Colombia, India, Pakistan, Tanzania, and Zimbabwe found that households primarily cooking with gas or electric stoves had the lowest average concentrations (45 and 53 $\mu g/m^3$, respectively) compared with households primarily using coal or wood (68 $\mu g/m^3$ and 109 $\mu g/m^3$, respectively) (14).

Household solid fuel burning is also estimated to be an important source of outdoor $PM_{2.5}$. While the proportion of ambient $PM_{2.5}$ from household solid fuel stoves varies regionally and seasonally (14), a 2008 study (72) estimated that household solid fuel stoves accounts for one-fifth of the yearly global average (population weighted) of outdoor $PM_{2.5}$.

2.3.2 Outdoor and household air pollution in China

Following its adoption of major economic reforms in the late 1970s, China's rapid economic development and urbanization resulted in a large-scale expansion of its energy and industrial sectors (73). These changes increased economic development but also resulted in widespread environment impacts, which is illustrated by the development strategy of *'pollute first, clean up later'* taken by the government over several decades (73, 74). High and increasing levels of air pollution were a ubiquitous environmental challenge across China by the early 1990s (75), which motivated the implementation of air quality guidelines in 1996. These were accompanied by some increases in air pollution monitoring but there was little enforcement (75, 76). China subsequently implemented a number of industrial pollution controls between 2000 and 2007 (77) which slowed the increase in $PM_{2.5}$ concentrations (77, 78), but the largest reductions occurred after 2013 when the government introduced an ambitious and multi-sectoral Air Pollution Prevention and Control Action Plan. The plan introduced new reduction targets for a number of pollutants including $PM_{2.5}$ and rigorously implemented and enforced new air pollution controls including industrial emissions regulations and the phasing out of older industrial boilers, improving gasoline and diesel quality, and encouraging industrial and residential shifts from coal to gas and electricity (77). Ambient levels of $PM_{2.5}$ in across China decrease by ~3 $\mu g/m^3$ per year between 2013 and 2018 (77). Large reductions in $PM_{2.5}$ (34-49%) were observed in the target regions of Beijing-Tianjin-Hebei, the Yangtze River Delta, the Pearl River Dealt, the Sichuan Basin, and the Xi'an during this same period (79). In 2019, China's annual estimated population-weighted $PM_{2.5}$ was 48 $\mu g/m^3$ (1), which is close to the China standard of 35 $\mu g/m^3$ but still well above the WHO annual guideline of 5 $\mu g/m^3$ (63).

Residential solid fuel burning for cooking, heating and other households tasks remains a common practice in China, especially in more rural and peri-urban areas, though the proportion of the Chinese households primarily using solid fuel has reduced considerably over the last decade, from 54% in 2010 to 36% in 2019 (1). This trend is partly attributable to rapid urbanization but also because rural and more remote areas of the country gained access to clean fuels through increasing incomes and advances in rural electrification and supply chains for LPG. Policies aimed at promoting household energy transition such as the coal-to-clean energy policy evaluated in Objectives 2 and 3 of this thesis have also played a role in clean energy transition (1). China decreased its residential coal consumption by about ~40% between

1990 and 2014 (80) though progress fluctuated with changes in price and availability impacting household coal use in northern China (80, 81). A multiprovincial cohort study (n=753) in China found that 35% of participants had transitioned from coal-to-clean energy for cooking whereas only 17% of households stopped use of coal for heating between the mid 1990s to the mid 2010s (82). Uptake of clean fuels was not always paired with a suspension of solid fuel use, and complete transition to clean energy was more common for cooking than for heating.

2.4 Cardiovascular Disease and Acute Myocardial Infarction

Cardiovascular disease is the leading cause of death globally, responsible for an estimated 20 million premature deaths in 2021 (44, 83), and is anticipated to increase as the global population ages (84). Cardiovascular disease refers to disease of the heart or blood vessels. Ischemic heart disease and stroke are the leading causes of cardiovascular death (83). Many cardiovascular diseases are the results of atherosclerosis, the accumulation of plaque in an individual's arteries, which decreases the flow of blood and stiffen the walls of the blood vessel (85). This leads to inadequate blood flow and oxygen to the heart or brain. If blood flow to the heart is blocked or greatly inhibited, generally due to an atherosclerotic plaque rapture, a myocardial infarction event occurs.

Acute myocardial infarction (AMI) is a type of acute coronary syndrome that occurs with sudden or short-term changes in blood flow to the heart. It accounts for one third of annual deaths in developed nations (86). Fatality rates from an AMI event are high, even in high-income settings with access to health care. For example, a muti-country surveillance study in New South Wales (Australia), Ontario (Canada), New Zealand and England observed fatality rates of 19 to 37% for AMI events in 2015 (87). Between 2013 and 2019, fatal AMI events comprised 34% of all AMI events in Beijing, a relatively wealthy province where residents have access to some of the best cardiovascular hospitals in China (88).

Efforts to reduce cardiovascular disease and related mortality include various primary and secondary prevention efforts. Primary prevention focused on lower risk factors associated with onset of cardiovascular disease such as lifestyle (e.g. diet, smoking and inactivity) or environmental (e.g. air pollution, low or high temperatures) risk factors. Secondary prevention is focused on reducing the adverse health impacts of the disease by limiting progression and damage. This can include lowering the same risk factors as in primary prevention, treatment (like statins or β-blocker), and early detection (89). These efforts are visible in the WHO's Global Action Plan for the prevention and control of noncommunicable diseases: 2013-2020 (90) which aims to reduce the global burden from noncommunicable diseases. In China, its ambitious Healthy China 2030 Plan aims to reduce the 2015 rate of premature mortality from cardiovascular disease by 30% through primary prevention and enhanced screening and treatment (91, 92).

2.4.1 The burden of cardiovascular disease and acute myocardial infarction in China

Cardiovascular disease is the leading cause of death in China (93), accounting for an estimated 5 million deaths (47% of deaths) in 2019 (94). Stroke (2.40 million deaths in 2019) and ischemic heart disease (2.06 million deaths in 2019) are the leading cause of cardiovascular disease deaths accounting for ~87% of China's cardiovascular disease deaths in 2019 (94). While the crude mortality rates from cardiovascular disease are still increasing in China, its age-standardized rates have decreased in recent years. For example, between 2015 and 2019 there was an increase of 7.4% in cardiovascular deaths but a 7.4% decrease in age-standardized death rates (95).

Rates of cardiovascular disease are higher in males than female (388 and 341 per 100,000 population in 2019, respectively) (95), with similar trends in ischemic heart disease and stroke, though these gender differences appear to be converging (96). Rural populations and those in northern China are also at higher risk (95, 97, 98), which are associated with geographic differences in dietary sodium intake, hypertension and hypertension-treated, smoking, and other behavioral factors (95). Rural areas in China experienced large increases in AMI mortality in the last decade with rates increasing from 11.3 per 100,00 population in 2005 to 74.7 in 2016 (97), and are now higher than in urban areas.

The large and increasing burden of cardiovascular disease appears to be due to a number of factors. This includes the 1) aging population, 2) high prevalence of risk factors, and 3) suboptimal prevention. The rapid aging of the Chinese population is at least partly responsible for the increase in incidence of and mortality from cardiovascular disease over the last decade (99-101). The percentage of the Chinese population over 60 years old increased from 10.5% in 2000 to 18.9% in 2021 (102). Rural areas are aging faster than the urban population, having a larger proportion of their populations above 60 years old (103). The high, and in some cases growing, prevalence of different lifestyle and environmental risk factors, such as obesity, high-salt diets, smoking, air pollution, and inactivity have increased cardiovascular risk in the Chinese population (97). Suboptimal levels of prevention of cardiovascular events due to underdiagnosed and undertreatment for early stage of cardiovascular conditions (e.g. hypertension) and suboptimal use of secondary prevention drugs also contribute to these trends (98, 104). In a nationally-representative health survey in China, one-third of the study had hypertension but only ~30% of them had been diagnosed (105). Of those diagnosed with hypertension only about half had been treated and of those treated, only 30% had their hypertension under control (105).

2.5 Estimated Global Burden of Disease from Air Pollution

Strong and consistent evidence from many countries associate air pollution with a wide range of health impacts across the life course including adverse birth outcomes and an increased incidence of cardio-respiratory diseases and – more recently – neurological diseases (1, 4, 27, 63). In 2019, air pollution (i.e., outdoor $PM_{2.5}$ and O_3 and indoor solid fuel use) was estimated to be the 4th leading contributor of premature death globally, responsible for an estimated 6.67 million deaths (1). Of these, 2.2 million deaths were attributed to household air pollution from indoor solid fuel use.

The estimated disease burden of air pollution is highly unequal, with the majority of estimated air pollution-related deaths occurring in LMICs (1, 106). This inequality persists after accounting for population aging and size, with age-standardized deaths per 100,000 being 5 to 12 times higher in LMICs compared with high-income countries (1). Global disparities in the estimated air pollution-related disease burden is growing in many LMICs, including India and China, as their populations age and are more susceptible to the chronic disease impacts of exposure to air pollution (1, 84, 107). From 1990 to 2019, the rate of age-standardized deaths attributed to outdoor $PM_{2.5}$ decreased in high-income countries (37 to 14 per 100,000 population) whereas deaths in LMICs increased during the same period. In low-and lower-middle income counties the rate of age-standardized deaths increased from 25 to 37 per 100,000 and 54 to 81 per 100,000, respectively (1). Age-standardized, air pollution-attributable mortality rates have decreased slightly in upper-middle income countries, but remain 4.5 times higher than in high-income countries (1).

2.5.1 Estimated burden of disease from air pollution in China

In 2019, an estimated 1.4 million deaths in China were attributed to ambient $PM_{2.5}$ and 0.4 million were attributed to household solid fuel use (1). While the rate of age-standardized deaths has decreased in China from 96.4 per 100,000 population in 2010 to 81.3 per 100,000 population in 2019, the absolute number of deaths due to ambient $PM_{2.5}$ have increased over the same period with population growth. Forty-three percent of China's air pollution-related deaths are attributed to cardiovascular disease and 24% of deaths are attributed to ischemic heart disease (95).

2.6 Air Pollution, Household Solid Fuel Use, and Cardiovascular Disease

Strong and consistent epidemiological and toxicological evidence indicates that exposure to $PM_{2.5}$ can increase the risk of developing cardiovascular disease including stroke and ischemic heart disease (108-110). While the proportional cardiovascular disease risks of air pollution are much lower than those of behavioral risk factors (e.g., tobacco use and inactivity) the population impacts of air pollution are enormous given the number of people exposed (1, 111, 112). Short-term (acute) exposure to elevated levels of $PM_{2.5}$ is associated with an increased incidence of myocardial infarction and stroke (26, 109, 110) and long-term exposure to $PM_{2.5}$

over many years can increase cardiovascular risk by an even larger magnitude (26, 113). Even in low pollution settings such as Canada, increases in $PM_{2.5}$ from 5 and 10 $\mu g/m^3$ are associated with progression in coronary calcification (114), increased risk of ischemic heart disease (115, 116), and cardiovascular mortality (115).

Most longitudinal studies of air pollution and cardiovascular disease were conducted in Europe and North America, though an increasing number of recent studies were conducted in China (117). In a recent systematic review of studies conducted in LMICs, long-term exposure to $PM_{2.5}$ was positively associated with cardiovascular mortality (effect estimate range: 0.2–6.1% per 10 $\mu g/m^3$) and with cardiovascular-related hospitalizations and emergency room visits (effect estimate range: 0.3–19.6% per 10 $\mu g/m^3$) (117).

Several studies separately evaluated the cardiovascular impacts of solid fuel stove use, which was measured through household surveys (5, 118-120). In China, use of solid fuel stoves was associated with a greater risk of cardiovascular mortality compared with gas users (range of hazard ratios (HRs): 1.20–1.29) (119). Most recently, a multi-country cohort study observed an increased risk of cardiovascular hospitalizations, fatal and non-fatal events, and cardiovascular mortality (range of HRs: 1.04–1.10) among users of solid fuel cookstoves (5). These studies are supported by studies of subclinical cardiovascular endpoints showing higher levels of inflammatory markers, blood pressure, and arterial stiffness in women using solid fuel stoves and with higher $PM_{2.5}$ exposures (118, 121-123).

Adding to this evidence are a growing number of randomized and non-randomized intervention studies that evaluated whether switching from solid fuel to less polluting electric or gas stoves could reduce cardiovascular risk. A 2019 systematic review concluded that shifting from biomass to gas stoves was associated with blood pressure reductions (124), though a more recent multi-country randomized trial observed a small increase in blood pressure among younger women assigned a gas stove compared with women who continued using solid fuel stoves (125).

The biological mechanisms connecting exposure to air pollution and cardiovascular disease risk are not entirely understood, through oxidative stress and inflammation are thought to play important roles (108, 126, 127). $PM_{2.5}$ is small enough that it can translocate from the lungs into the circulatory system after inhalation. Exposure to $PM_{2.5}$ can induce inflammatory and oxidative stress responses, which are underlying mechanisms for cardiovascular disease and other chronic diseases (26, 113). Short-term exposure to high air pollution can lead to acute ischaemic (when blood and therefore oxygen flow is restricted) events and therefore AMI events by increasing systolic blood pressure leading to plaque ruptures in individuals already at risk of AMI. Long-term exposure increases the probability of a rupture by leading to the plaque build-up and affecting stability of the plaque that is deposited.

2.7 A Brief History of Household Energy Policies and Programs

A number of countries including China, India, Ecuador, and Rwanda have implemented clean energy policies to reduce air pollution and health impacts (128). The policies vary considerably in the technology and/or fuel being promoted and implementation, but generally have the shared goal of motivating a shift from traditional solid fuel stoves to more efficient household stoves (e.g., improved combustion solid fuel stoves) or to cleaner burning fuels (e.g. gas and electricity). Clean energy transition has implications beyond pollution and health, with potential co-benefits including less time spent harvesting fuel (a burden often borne by women and girls) and reductions in deforestation and biodiversity loss from solid fuel extraction (129, 130).

Early clean energy programs in the 1980s and 1990s focused on the implementation of more efficient versions of solid fuel stoves, usually distributed through development projects. The stoves were primarily designed to burn less wood and thus yield reductions in fuelwood extraction from local forests (131). For example, in response to widespread deforestation and rural biomass shortages in China in the 1980s, the Chinese government organized the world's largest publicly-financed initiative to improve stove function -- the National Improved Stove Program (NISP). The program provided over 130 million rural households with more efficient biomass stoves and, later, new coal stoves. The new stoves were generally well-used and liked by households (132). Many rural Chinese households still use versions of these biomass stoves at present. While the biomass stoves did provide a small reduction in household $PM_{2.5}$ compared with open fires, they still emitted high levels of pollution and the new coal stoves actually increased emissions (133). In other countries, the improved biomass stoves were quickly abandoned by many households because they were not sufficiently robust for daily use, did not sufficient meet cooking or heating needs, or required households to do additional preparation like chop fuelwood into very small pieces (134).

More recent energy policies promote cleaner-burning fuels (e.g., gas and electric-fueled stove technologies). For example, the Ecuadorian Programa de Cocción Eficiente aims to transition 3.5 million households from cooking with LPG to electric induction stoves by 2023 through a voluntary financial program (128) and Rwanda's Energy Sector Strategic Plan includes plans to provide electricity to over 2 million households along with various clean cooking options (128, 135). Some of these energy policies include regulatory elements, such as banning use of solid fuel; awareness campaign; financial incentives; and infrastructure investments (e.g. increasing the electric grid capacity).

The adoption of these policies has been mixed. In Ecuador, the policy failed to recruit its target of 3.5 million households by 2018, recruiting just 740,000 households (136). Satisfaction with the new stoves was also low (136). The Ujjwala program in India has promoted LPG in low-income households in rural India through financial support to help cover the LPG connection (LPG stove and registration) (137). This program has led to an increase in households with an LPG connection but not a large increase in LPG sales suggesting continued use of solid fuels (137). LPG has a positive perception and is widely used in India but cost is still a limiting factor in its adoption and exclusive and long-term use (138).

2.8 The Beijing Coal-to-Clean Energy Program

Recognizing the population health impacts of air pollution, the national and provincial-level governments in China implemented several policies across multiple sectors that were aimed at reducing air pollution, most ambitiously after 2013, as described in Section 2.3.2. Reducing coal burning in the industrial and residential (household) sectors has been a large component of these action plans (**Table 1**) (1, 66, 139).

Table 1: Recent policies aimed at reducing residential coal burning affecting Beijing

Policy	Year enacted	Aim
Air Pollution Prevention and Control Action Plan	2013	Created high-quality coal distribution centers and increased the accessibility of natural gas and electricity in rural areas through infrastructure improvements
Strengthening Measures for Jing-Jin-Ji Air Pollution Prevention (2016–2017)	2016	Banned coal in defined areas and aimed to eliminate coal use in the plains region by 2017
Work Plan for the Control of Greenhouse Gas Emissions during the 13th Five-Year Period	2016	Accelerated the expansion of the residential coal-to-clean energy policy to more rural and remote areas
Work Plan for Air Pollution Prevention and Control in Jing-Jin-Ji and Surrounding Areas in 2017	2017	Targeted 50,000–100,000 peri-urban and rural households to transition from coal to gas or electric powered heaters. New residential homes had to accommodate clean fuel use
Notice of the National Energy Administration (NEA) on the Implementation of the Central Financial Support for the Winter Clean Heating in Northern Region	2017	Provided financial support for municipalities to assist households in starting to use clean heating fuels through subsidies for new stoves and electricity
Action Plan of Comprehensive Management of Air Pollution for Jing-Jin-Ji and Surrounding Areas in the Autumn and Winter of 2017–2018	2017	Targeted 3 million peri-urban and rural households to transition from coal to electric and/or gas heaters by 2017 and promoted higher-quality coal in areas that could not participate in the coal-to-clean energy policy
Clean Warm Winter Planning in the Northern Region (2017–2021)	2017	Set clean energy targets for northern China. By 2019 and 2021, 50% and 70%, respectively, of households should transition to gas or electric heaters

Notice on Expanding the Central Financial Support for the Winter Clean Heating Pilot City in the Northern Region	2018	Provides financial support to municipalities to support residential coal-to-clean energy transition through subsidies for new stoves and electricity
Three-year action plan for Winning the Blue-Sky Defense War	2018	Transition to clean energy should be completed earlier (by 2020) and proposes enforcement of use of high quality coal in areas not using gas and electric heaters
Action Plan of Comprehensive Management of Air Pollution for Jing-Jin-Ji and Surrounding Areas in the Autumn and Winter of 2018–2019	2018	Planning for continued use of gas and electric heaters amidst anticipated gas shortages while avoiding to inadequate heating and enforces bans on low-quality coal

Note: This table is adapted from a table in Wu et al. (2020) (139)

Starting in 2016, the Beijing government began the large-scale transition of rural and peri-urban households from coal-to-clean burning fuels including electricity and gas (140)[1], which was in line with national and regional mandates. The coal-to-clean energy policy was first implemented in areas with better infrastructure including updated electrical grids and gas lines. The policy banned the use of coal and to motivate this transition, the government instituted a subsidy program for the purchase and installation of electric or natural gas-powered heaters and provided rural areas with access to subsidized electricity prices (same as urban users) and subsidized gas prices for up to three years (140, 141). The overarching goal of this transition was to reduce air pollution while meeting the indoor heating demands of the rural populations. A further benefit of these programs may be an increase in indoor household temperature during winter (141) though other studies indicate the this benefit is limited to wealthier households (139).

[1] This is outlined in the policy documents: *Beijing 2016 Implementation Plan for "Coal to Clean Energy and Coal Reduction and Replacement" in Rural Areas* and *Beijing 2016−2020 Work Plan for Accelerating the Promotion of Clean Energy Replacement of Civilian Coal*

2.9 The Need for Impact Evaluation of Household Energy Policies

Clean energy policies and interventions are generally assumed to improve environment and health, but empirical assessments are rare. Most evaluations are limited to randomized trials or non-randomized (but investigator-driven) intervention evaluations that include several hundred households (142). While improved biomass stoves and clean fuel have generally resulted in some indoor air quality improvement (16, 143, 144) the health benefits are less clear. A recent multi-country randomized trial found an increase in gestational blood pressure (systolic: 0.69 mmHg; diastolic: 0.62 mmHg) in women in household receiving an LPG stove compared with women using traditional biomass stoves (125), despite a large decrease in median 24-h personal exposure to $PM_{2.5}$ among women in the intervention arm (from 84 to 24 $\mu g/m^3$).

Impact assessments (also referred to as accountability studies) are empirical studies that estimate the impact of an invention by comparing the air quality or health outcome from pre and post invention periods and/or control groups. When well-conducted, these studies can provide rigorous evidence of the effectiveness of an intervention and are the closest to a controlled experimental study. Systematic reviews by Burns et al. (2020) and Rich (2017) and my own search of the literature identified only a handful of impact assessments that empirically assessed the environmental and health impacts of such policies (45, 145), nearly all of which were conducted in high-income countries.

Most of these studies were evaluating residential clean energy policies in high-income countries (**Table 2**), including a series of coal bans in Ireland in the 1990s and 2000s (45, 146), a wood-burning stove exchange program in Central Launceston, Australia (147), an air quality-dependent wood burning ban in the San Joaquin Valley Air Basin, USA (148), a ban on solid fuel burners and open fires paired with a residential clean heater replacement program in Christchurch and Timaru, New Zealand (149), and a policy subsidizing LPG in Ecuador (150). These studies compared the pre and post levels of air pollution and/or health outcomes. While these studies generally provide evidence of air quality improvements, the evidence for health benefits of the policies was limited.

Objectives 2 and 3 of my thesis evaluate the air quality and cardiovascular impacts of the coal-to-clean energy program in Beijing. Large-scale clean energy policies like this one in Beijing provide the opportunity for evaluation to better understand whether these policies are successful in achieving their intended benefits.

Table 2: Large-scale residential clean energy policies and their effects on air pollution and health

Location	Population and time period	Invention	Outcomes	Results
Ireland *Dockery et al. (2013)*	Populations of Dublin and 11 other Irish cities from 1981 to 2004	Coal ban	• Black smoke and total gaseous acidity • All-cause mortality • Cardiovascular mortality • Respiratory mortality	Black smoke concentrations decreased by 45-70% but there was no observable change in total gaseous acidity No reduction was found in all-cause or cardiovascular mortality A 17% reduction was seen in respiratory mortality with the ban in Dublin but this impact was much reduced in other cities that entered the ban
Central Launceston, Australia *Johnston et al. (2013)*	Population of Launceston from 1994-2000 (pre) and 2001-2007 (post)	Wood-burning stove exchange program	• PM_{10} • All-cause mortality • Cardiovascular mortality • Respiratory mortality	Mean daily wintertime PM_{10} concentrations decreased by ~40% Large and significant reduction in all-cause, cardiovascular, and respiratory were only seen in males with reductions of -11%, 18%, and 23% respectively
Christchurch and Timaru, New Zealand (149) *Scott and Scarrott (2011)*	Populations in Christchurch and Timar from 2001 to 2009	Ban on solid fuel burners and open fires paired with a residential clean heater replacement program	• PM_{10}	35% and 26% decrease in winter mean and median PM_{10} respectively in Christchurch 11% and 3% decrease in winter mean and median PM_{10} respectively in Timaru

San Joaquin Valley Air Basin, USA (148) *Yap and Garcia (2015)*	Adults living in the San Joaquin Valley Air Basin divided into two age groups 45–64y and 65y+ from 2000-2003 (pre) and 2003-2006 (post)	Air quality-dependent wood burning ban	• $PM_{2.5}$ and PM_{10} • Cardiovascular disease hospital admissions • Ischemic heart disease hospital admissions • Chronic obstructive pulmonary disease (COPD) hospital admissions	Decrease of 12% and 8% in $PM_{2.5}$ and PM_{10} Hospital admissions for cardiovascular disease and ischemic heart disease decreased by 7% and 16% in adults 65y+ There was no clear change in COPD admissions or cardiovascular disease and ischemic heart disease hospital admissions for adults aged 45-64y
Ecuador (150) *Gould et al. (2023)*	Nationally population divided in 167 cantons across four time periods: 1988-1992, 1999-2003, 2008-2012, and 2015-2019	Subsidized LPG program	• Under-5 lower respiratory infection mortality	20% decrease in under-5 lower respiratory infection mortality during study period (28 to 7 per 100,000)

Chapter 3: Objective 1

3.1 Preface

This chapter contains the first objective of my thesis. This multi-provincial study examines 1) the seasonal variation and levels of personal exposure in men and women living in rural and peri-urban China, 2) the within- and between-individual variability in daily personal exposure to air pollution, and 3) the associations of socio-demographic factors and different indoor and outdoor sources, like residual fuel use and outdoor air quality, with personal exposure. In this study, we conducted repeated measurements of daily personal exposure to $PM_{2.5}$ and black carbon in 787 men and women (ages 40–79) living in rural and peri-urban villages in northern (Beijing and Shanxi) and southern (Guangxi) China, with up to 4 days of repeated measures for each participant. We simultaneously measured outdoor $PM_{2.5}$ and collected questionnaire data on sociodemographic characteristics and indoor pollution sources including tobacco smoking and solid fuel stove use. These data were used in a series of linear mixed effect models to estimate the within- and between-individual variability in exposure and the variables associated with both variability and levels of exposure.

This objective adds to the theme of this thesis showing the challenge of measuring exposure to household air pollution for epidemiologic and intervention studies given the high within-individual variability in daily exposure. It provides an understanding of the impact of residual fuel use type on personal exposure to air pollution in the Chinese context of high outdoor air pollution and high smoking rates. Estimating the benefits of different air pollution mitigation strategies requires an understanding of the source contributors to personal exposure as the air quality benefits of clean energy transition may be masked by the large contributions of other proximal air pollution sources. This manuscript is peer-reviewed and published in *Environment International.*

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3.2 Determinants of Personal Exposure to $PM_{2.5}$ and Black Carbon in Chinese Adults: A Repeated-Measures Study in Villages Using Solid Fuel Energy

Abstract

Exposure to air pollution is a leading health risk factor. The variance components and contributions of indoor versus outdoor source determinants of personal exposure to air pollution are poorly understood, especially in settings of household solid fuel use. We conducted a panel study with up to 4 days of repeated measures of integrated gravimetric personal exposure to $PM_{2.5}$ and black carbon in 787 men and women (ages 40-79) living in peri-urban villages in northern (Beijing and Shanxi) and southern (Guangxi) China. We simultaneously measured outdoor $PM_{2.5}$ and collected questionnaire data on sociodemographic characteristics and indoor pollution sources including tobacco smoking and solid fuel stove use. We obtained over 2000 days of personal exposure monitoring which showed higher exposures in the heating season (geometric mean (GM): 108 versus 65 $\mu g/m^3$ in the non-heating season for $PM_{2.5}$) and among northern participants (GM: 90 versus 59 $\mu g/m^3$ in southern China in the non-heating season for $PM_{2.5}$). We used mixed-effects models to estimate within- and between-participant variance components and to assess the determinants of exposures. Within-participant variance in exposure dominated the total variability (68-95%). Outdoor $PM_{2.5}$ was the dominant variable for explaining within-participant variance in exposure to $PM_{2.5}$ (16%). Household fuel use ($PM_{2.5}$: 8%; black carbon: 10%) and smoking status ($PM_{2.5}$: 27%; black carbon: 5%) explained the most between-participant variance. Indoor sources (solid fuel stoves, tobacco smoking) were associated with 13-30% higher exposures to air pollution and each 10 $\mu g/m^3$ increase in outdoor $PM_{2.5}$ was associated with 6-8% higher exposure. Our findings indicate that repeated measurements of daily exposure are likely needed to capture longer-term exposures in settings of household solid fuel use, even within a single season, and that reducing air pollution from both outdoor and indoor sources is likely needed to achieve measurable reductions in exposures to air pollution.

Introduction

Air pollution is a leading global concern for human health (66). Exposure to fine particulate matter ($PM_{2.5}$) air pollution is independently associated with the development of cardio-respiratory diseases and other adverse health outcomes throughout the life course including low birth weight and neurocognitive outcomes (66, 151). Air pollution ranks as the 5th leading risk factor for global mortality, responsible for an estimated 4.9 million premature deaths in 2017 (66). Low- and middle-income countries comprise a substantial share of this burden, accounting for over 90% of $PM_{2.5}$-attributable deaths (66).

The source contributors to air pollution are diverse, even in rural and peri-urban settings (152). Outdoor emissions sources like traffic, industry, and agricultural burning are large contributors to $PM_{2.5}$ in these settings (33, 34). Indoor sources like tobacco smoking and household use of solid fuel stoves (used in 47% of homes globally for cooking) emit high levels of $PM_{2.5}$ into homes and communities (66). The relative contribution of indoor versus outdoor sources to exposures to $PM_{2.5}$ is poorly understood, particularly in low and middle-income countries, in large part due to the relatively few studies with measured personal exposures (43). Understanding the determinants of exposure has important implications for air pollution interventions and policies. Recent intervention studies, for example, hypothesized that pollution from traffic and poor outdoor air quality limited the effectiveness of household stove interventions in measurably reducing exposures to $PM_{2.5}$ (16, 152-155).

Although an increasing number of studies have measured personal exposures to $PM_{2.5}$ in settings of solid fuel burning (7), very few have included repeated measures of exposure (8-12). Instead, most studies involved a single short-term (24- or 48-h) measurement (43) and focused on $PM_{2.5}$ mass but were unable to evaluate specific components of PM that could indicate its toxicity (e.g., black carbon). This limits our understanding of how to best assess 'usual' exposure to air pollution in settings of household solid fuel use, which is the metric most relevant for epidemiologic and intervention studies. There is also a lack of air pollution exposure data for important population subgroups. Men, for example, account for nearly half of the modelled disease burden attributable to household air pollution (156), but few studies have measured men's exposure to $PM_{2.5}$ in a setting where solid fuel stoves were used (11, 13, 14). Measurements of $PM_{2.5}$ exposures in exclusive clean fuel users relative to users of solid fuel in the same setting are rare, which is important for more realistically estimating the potential air quality and health benefits of clean energy interventions (7, 14).

Leveraging 2246 measurement days of personal exposure to $PM_{2.5}$ and black carbon from 787 participants enrolled in the INTERMAP China Prospective (ICP) study, this study aims to 1) characterize the levels and seasonal patterns of air pollution exposures for men and women living in northern and southern China, 2) describe the variability in exposures within- and between-participants, and 3) evaluate the contribution of indoor and outdoor sources of air pollution to personal exposures.

Methods

Study design and population

The ICP study design and population are described in detail elsewhere (157). In brief, 787 adults (ages 40-79, 55% female) from 17 villages in three provinces in northern (Beijing, Shanxi) and southern (Guangxi) China were enrolled into the study in 2015 and 2016 (**Figure S1**). These regions were selected for study because of their diversity in geography and environmental risk factors for disease, including household fuel use. Coal fuel is commonly used for residential heating in northern China and is a large contributor to household and outdoor air pollution (34, 66), whereas the southern province of Guangxi is sub-tropical and does not have a distinct heating season. Biomass (i.e., wood and crop residues) stoves are used for cooking in all three sites, often alongside low-polluting electric and gas-powered stoves. Detailed information on household energy use practices in our study homes is published elsewhere (82).

Most ICP study participants were originally enrolled into the International Study of Macro/Micronutrients and Blood Pressure (INTERMAP), a cross-sectional study which randomly selected households in the study villages between 1995 and 1997, and then randomly selected one adult from each household to participate. We re-enrolled 575 of the 680 surviving INTERMAP participants (85% participation rate) into the ICP study (ages 60-79; 53% female), in addition to 212 adults (88% participate rate) ages 40-59 that were randomly selected from the same villages to evaluate cohort differences in environmental risk factors over time. We obtained written informed consent from all participants. Ethical approvals were obtained from all investigator institutions (McGill: #A08-M37-16B; Fu Wai Hospital: #2015–650; Imperial: #15IC3095, Peking: #00001052-15017, Tsinghua: #20140077).

Data collection

Measurement campaigns were conducted in Shanxi in August 2015 and November 2015; Beijing in December 2015 and September 2016; and in Guangxi in November 2016. We conducted two campaigns in the northern sites to capture the heating and non-heating seasons, which can impact household energy use and air pollution exposures (43).

For data collection, participants travelled to clinics that were centrally located in their villages, typically by foot or electric bicycle. Trained staff carried out the study measurements using the same standardized procedures across all sites (157). At the first clinic visit in each campaign, participants were fitted with personal air monitors and completed questionnaires on individual and household characteristics including energy use. Participants returned to the clinic after 24-h to exchange the air monitors for new ones and returned again after a second 24-h period to return their monitors. Staff conducted home visits if participants was unable to travel to the clinics. Outdoor air quality and ambient temperature were measured throughout the campaigns. Descriptions of these study measurements are summarized below and detailed information is published elsewhere (157).

Personal exposure to $PM_{2.5}$

We obtained 2246 measurements of integrated 24-h exposure to $PM_{2.5}$ using Harvard Personal Exposure Monitors (H-PEM) (Mesa Labs, USA) that housed Zefluor^{TM} 37mm PTFE filters (Pall Life Sciences, USA) and were attached downstream from a personal sampling pumps (Apex Pro and

TUFF™, Casella Inc; USA) operated at 1.8 L/min (158). Air monitors were placed inside waistpacks that participants were asked to wear at all times possible and to keep within 2 m while sleeping, sitting, or bathing (**Figure S2**). In a subsample of exposure measurements (n=1595, 76% of all measurements), we added a pedometer (HJ-321 Tri-Axis, Omron; Japan) to the waistpack to monitor compliance in wearing them. Participants with 24-h step counts of <500 steps were considered potentially non-compliant in wearing the air monitor on that day (n=47, 3%).

Pump flow rates were measured at the start and end of each sampling period using a rotameter that was field calibrated at the beginning and middle of each measurement campaign using a primary gas flow standard (mini-BUCK Calibrator M-5; A.P. Buck Inc.; Orlando, FL, USA). For quality control and to address potential contamination, we collected ~7% field blank filters that were placed inside identical H-PEMs and cyclones, subject to the same field conditions, and analyzed using the same protocol as the filter samples.

Outdoor $PM_{2.5}$

We obtained real-time outdoor $PM_{2.5}$ measurements for our study period from nearby government air monitoring stations equipped with reference-quality monitors (i.e., tapered element oscillating microbalance (TEOM); (http://beijingair.sinaapp.com). Hourly data from all stations within 50 km of the village centers were inverse distance weighted (power function of 1) to calculate a mean hourly concentration for each study village. We then calculated 24-h average outdoor $PM_{2.5}$ values that corresponded with the date and time of the personal 24-h exposure measurements. Personal exposure measurements generally started at 10:00am and ended at 10:00am of the next day so outdoor $PM_{2.5}$ averages ran from 10:00am to 10:00am of the next day. We also measured village-level integrated gravimetric $PM_{2.5}$ during one data collection campaign at each study site. The gravimetric monitors were positioned at least 4 meters from the ground in a location that was 1) central to each village, 2) at least 30 meters from a household chimney, and 3) at least 100 meters from other $PM_{2.5}$ emission sources including local industry and major roadways. We placed PTFE filters into either H-PEMs or cyclones (Mesa Laboratories, USA) that were attached to sampling pumps with flow rates of 1.8 or 3.5 lpm, respectively. The filters were collected every 24-h and replaced with new ones. Village-level measurements of $PM_{2.5}$ were highly correlated with values estimated from government sensors on the same day (n=42 days of paired observations; Pearson r=0.87; RMSE = 45.4) (**Figure S3**). To quantify outdoor $PM_{2.5}$, we used the village-level measurements when available (34% of study days) and used the estimated $PM_{2.5}$ values for the remaining days.

Laboratory analysis of PTFE filters for $PM_{2.5}$ and black carbon

Gravimetric analysis was used to determine the $PM_{2.5}$ mass on filter samples and blanks. Following at least 24-h of conditioning in a temperature and humidity-controlled environment at the Wisconsin State Hygiene Laboratory (Madison, WI), the filters were weighed in duplicate using a microbalance (MX-5; Mettler-Toledo, Columbus, OH, USA). If the difference between the first two weights exceeded 15μg, a third measurement was obtained, and the two closest weights were averaged for statistical analysis. The microbalance's zero and span were checked after every batch of 10 filters. Pre-sampling filter weights were subtracted from the post-sampling weights. The filter mass (μg) was divided by the volume of air (m^3) pulled through the filter during sampling to calculate the $PM_{2.5}$ concentration.

Black carbon was measured on filters using an Aethalometer (SootScan™ Model OT21 Transmissometer, Magee Scientific; USA). Black carbon is a component of $PM_{2.5}$ and a product of incomplete combustion that may more strongly associated with adverse health outcomes than the mass of $PM_{2.5}$ (30, 159). The optical method estimates black carbon by evaluating the attenuation of light through the sample and blank PTFE filters compared with that of a reference filter. To equate the optical black carbon measurements to elemental carbon, we applied the U.S. EPA sigma of 4.2 and used an empirical correction factor based on the black carbon-elemental carbon associations in previous air pollution campaigns in rural China that used the same filter media (123). Specifically, we applied the linear correction factor of 0.092 with adjusted observed values ranging from 0.0085 – 11.4 μg/m^3. The corrected black carbon mass loadings (μg/cm^2) were converted to concentration (μg/m^3) by multiplying the mass loading (µg/cm^2) by the area of each filter (9.03 cm^2), and then dividing the mass by the volume of air sampled (m^3).

Season-specific blank values for $PM_{2.5}$ and black carbon were calculated for each study site and subtracted from the net filter weights and attenuated infrared values, respectively. We replaced negative blank-corrected values ($PM_{2.5}$: n=15 filters, <0.01%; black carbon: n=33 filters, <1%) by randomly assigning a value between 0 and half the limit of detection, which was 4 µg for $PM_{2.5}$ and 0.22 µg/m^3 for black carbon. We excluded filters from the statistical analysis if they were damaged (n=3 for $PM_{2.5}$ and n=1 for black carbon; <0.01% of filter samples); could not be matched to a participant due to data entry errors (n=21; <0.01%); had net weights that exceeded a realistic 24-h mass, indicating infiltration of larger-sized particles onto the filter, filters being switched, or unseen filter damage (n=7; <0.01%); or failed to capture at least 10-h of the 24-hr target due to pump failure (n=108; 4.8%). An unrealistic weight was defined as net weights less than 0 µg or over 2500 µg. Filters exceeding these weights were flagged and assessed for any abnormalities (e.g., filter damage or visible dust). For the main analysis, we used a 10-h cut-off for completeness because this time period captured most of the daytime hours. Of the 148 samples that ran for less than 23 hours but more than 10 hours, 70 ran for 10 to 19.2 hours (19.2 hours = 80% of the 24-h sampling time), and 78 samples ran between 19.2 and 23 hours. The remaining filter-based measurements were considered ‘complete’ and included in the statistical analysis.

Meteorological data

We obtained real-time temperature and dew point temperature data from the U.S. National Oceanic and Atmospheric Administration (https://www.ncdc.noaa.gov/isd/products). Relative humidity was estimated based on the temperature and dew point temperature the using the *weathermetrics* package in R (160). We used inverse distance weighting (power function of 1) from all meteorological stations within 100 km of each study village to estimate the daily temperature and relative humidity. To evaluate the accuracy to these data, we compared them to the outdoor temperatures measured during the participants clinic visits using local meteorological stations (157) (n=99 days; Pearson *r*=0.97; RMSE = 4.5) (**Figure S4**). We used the estimated temperatures for statistical analysis because they were highly correlated with measured temperature and also allowed us to more accurately time-match meteorological data with air pollution exposure measurements.

Questionnaires

Staff administered questionnaires in Mandarin-Chinese to collect information on variables potentially related to energy use and exposures to air pollution including age, gender, ethnicity, education, occupation, marital status, tobacco smoking, and household income. We drew questions from the INTERMAP study that were re-tested with local residents to ensure that questions were being interpreted as intended (157). We also collected comprehensive information on household fuels, energy devices, and ventilation using an image-based questionnaire that included pictures of all stoves and fuels used in the region. Detailed information on the energy questionnaire is provided elsewhere (82). Briefly, respondents indicated whether they were currently using a given energy device or fuel and, if so, described the frequency and purpose of use. Energy devices that burned coal, wood, and/or agricultural residues were categorized as 'solid fuel' stoves, while stoves powered by gas or electricity were considered 'clean fuel' stoves. All devices were classified into one of the following categories: solid fuel cookstoves, clean fuel cookstoves, solid fuel heating stoves, and clean fuel heating stove. Participants were categorized as 'exclusive clean cooking fuel' users if they reported using clean fuel regularly and reported no use or rare use (i.e., holidays or when hosting guests) of solid fuel. The remaining participants were classified as users of solid fuel for cooking. Solid fuel stove use was further divided into any indoor use or only outdoor use. Heating fuel included the same categories as cooking with the addition of a fourth category to indicate no heating or cooling-specific device in the home. For cooking fuel, outdoor-only solid fuel use and indoor solid fuel use were combined into a single category due to a small sample size.

Statistical analysis

Air pollution summary statistics were calculated by season, study site, gender, and energy use. Pollution exposures exhibited positive skewness, whereas the corresponding natural log-transformed values were approximately normally distributed and were thus used for statistical analyses. We evaluated whether measurement sequence may have systematically impacted exposure using scatterplots and paired t-tests that compared the first and second measurement day for each season and site.

Estimating with-individual and between-individual exposure variability

We used a series of mixed-effects regression models to leverage the repeated measures of air pollution and partition the total variance in exposure into its within-individual and between-individual components. We started with the following base (intercept-only) model:

$$\ln(Y_{ik}) = \beta_0 + b_i + \varepsilon_{ik}$$

where $ln(Y_{ik})$ is the k^{th} measurement of log-transformed pollution ($PM_{2.5}$ or black carbon) for participant i, b_i is the participant random effect and ε_{ik} is the remaining error with variance components of σ_b^2 and σ_ε^2, respectively. These can be roughly interpreted as the variance between-individuals (σ_b^2) and the variance within-individuals (σ_ε^2). We estimated the intraclass correlation coefficient (ICC; i.e., the proportion of total variability in exposure attributed to between-individual differences) by: $\sigma_b^2/(\sigma_b^2+ \sigma_\varepsilon^2)$. These models assume that the b_i and the ε_{ik} are independent and normally distributed with variances of σ_b^2 and σ_ε^2, respectively, and have a compound symmetry correlation structure.

Explaining variability in exposure to $PM_{2.5}$ and black carbon

We evaluated the proportion of each variance component explained by indoor and outdoor sources of air pollution and by other socio-demographic and environmental variables by comparing the base (intercept-only) model to a set of models containing an increasing number of independent variables. We evaluated variables that were determined *a priori* to be associated with exposure to air pollution in past studies (see variables listed in **Table 1**) (12, 161). We imputed missing data on yearly income for 93 participants (12%) using multiple imputation with the MICE package in R (162). Separate models were conducted for exposure to $PM_{2.5}$ and black carbon.

To assess the models' explanatory power and the fit of data, the proportion of within-individual variance explained (R^2_{within}) was calculated by subtracting from 1 the ratio of residual within-individual variance under each alternative mixed model to that of the base model, as described elsewhere Xu (163). Between-individual variance explained ($R^2_{between}$) was calculated in an analogous way. To evaluate the prediction accuracy of these models, we excluded a random 20% subsample of observations to create the appearance of missing data. The remaining data were used to estimate the full model with all covariates and then predict the excluded observations. We ran each model 100 times, each run dropping a different random 20% subset of the data. For each model run, we calculated the root mean square error (RMSE) and Spearman correlation between predicted and measured exposures. The final estimates are the averages of 100 model runs.

The linear mixed-effects regression models were conducted in R (R Core Team, 2013, version 3.4.2) using the *lme* function from the *nlme* package (164). Collinearity among the independent variables was investigated using Pearson correlation matrices and variance inflation factors, and the assumptions of normality of residual errors and homoscedasticity were evaluated by graphical analysis of the residuals. To assess assumptions of linearity for continuous independent variables, we generated response functions using natural cubic spline models with 2 and 3 degrees of freedom (165), (166). All response functions were consistent with a linear association and thus replaced by linear functions. Marginal and conditional R^2 values (167) were calculated to compare the results from the $PM_{2.5}$ and black carbon prediction models.

We conducted a number of sensitivity analyses for the $PM_{2.5}$ modelling. We conducted separate models by gender and season and also limited the analysis to exposure observations where the measurement duration was within ±10% of the 24-h target (n=1969; 95% of observations). To assess whether use of outdoor $PM_{2.5}$ from the government monitors versus village-level measurements impacted our results, we restricted the regression analyses to exposure measurements taken on the same day as village-level outdoor $PM_{2.5}$ (n=619; 30% of observations), and compared those results to models including outdoor $PM_{2.5}$ from government monitors. To assess potential non-compliance in wearing the personal samplers, we restricted the regression analyses to samples with associated step counts greater than 500 steps.

Results

Characteristic of the study participants

Participants ranged in age from 40 to 79 years (mean: 63) and were 55% female (**Table 1**). Most participants in the north (Beijing, Shanxi) were subsistence farmers (76%), while most participants in Guangxi were either retired or not working (73%). Exclusive use of clean fuel for cooking (48%) was more common than exclusive use of clean fuel for heating (38% among those reporting space heating). Nearly half (49%) of men were tobacco smokers. Very few women smoked (2%), though 45% of non-smoking women lived with at least one smoker.

Table 1: Characteristics of study participants by study site [n (n%) or mean (standard deviation, sd)]

Characteristic	Guangxi (n=239)	Beijing (n=258)	Shanxi (n=290)
Age (years), mean (sd)	63.4 (9.4)	63.6 (7.6)	62.0 (8.7)
Gender			
female	128 (53.6)	149 (57.8)	157 (54.1)
male	107 (44.8)	108 (41.9)	133 (45.9)
missing	4 (1.7)	1 (0.4)	0
Ethnicity			
Han	122 (51.0)	255 (98.8)	290 (100.0)
Zhuang	113 (47.3)	0	0
other	0	2 (0.8)	0
missing	4 (1.7)	1 (0.4)	0
Occupation			
subsistence farming	34 (14.2)	200 (77.5)	213 (73.4)
other work outside the home	30 (12.6)	15 (5.8)	21 (7.2)
not working outside the home[a]	171 (71.5)	42 (16.3)	56 (19.3)
missing	4 (1.7)	1 (0.4)	0
Martial status			
married/cohabitation	175 (73.2)	229 (88.8)	255 (87.9)
widowed	51 (21.3)	24 (9.3)	31 (10.7)
divorce/separated/unmarried	9 (3.8)	4 (1.6)	4 (1.4)
missing	4 (1.7)	1 (0.4)	0

Household income in the past year			
<2000 yuan	29 (12.1)	135 (52.3)	199 (68.6)
≥2000 yuan	206 (86.2)	122 (47.3)	91 (31.4)
missing	4 (1.7)	1 (0.4)	0
Highest education attained			
no formal education	29 (12.1)	61 (23.6)	30 (10.3)
primary school	101 (42.3)	86 (33.3)	137 (47.2)
early high school/college	105 (43.9)	110 (42.6)	123 (42.4)
missing	4 (1.7)	1 (0.4)	0
Tobacco smoking			
current smoker	40 (16.7)	56 (21.7)	85 (29.3)
non-smoker w/ household smoker	59 (24.7)	77 (29.8)	72 (24.8)
non-smoker w/o household smoker	136 (56.9)	125 (48.4)	133 (45.9)
missing	4 (1.7)	0	0
Fuel used for cooking[b]			
exclusive clean fuel	69 (28.9)	163 (63.2)	129 (44.5)
solid fuel, indoor	154 (64.4)	81 (31.4)	155 (53.4)
solid fuel, outdoor only	1 (0.4)	1 (0.4)	0
missing	15 (2.1)	13 (5.0)	6 (2.1)
Fuel used for space heating[b]			
exclusive clean fuel	70 (29.3)	61 (23.6)	88 (30.3)
solid fuel, indoor	0	170 (65.9)	151 (52.1)
solid fuel, outdoor only	0	11 (4.3)	29 (10.0)
no device	154 (64.4)	3 (1.2)	16 (5.5)
missing	15 (2.1)	13 (5.0)	6 (2.1)

a Includes housekeeping, retired, and unemployed

b Clean fuel includes natural gas, liquified petroleum gas (LPG), and electricity; solid fuel includes coal and biomass. For cooking fuel use, participants were assigned to the following categories: (1) exclusive clean fuel (i.e., use of gas or electricity and no or only rare use of solid fuel (i.e., holidays or when hosting guests); (2) solid fuel, indoor stove (i.e., use of at least 1 solid fuel stove indoors), or (3) solid fuel, outdoor only (i.e., use of solid fuel stove but only outdoors). For heating, we added the additional category of “no device” (i.e., no heating-specific devices in the home).

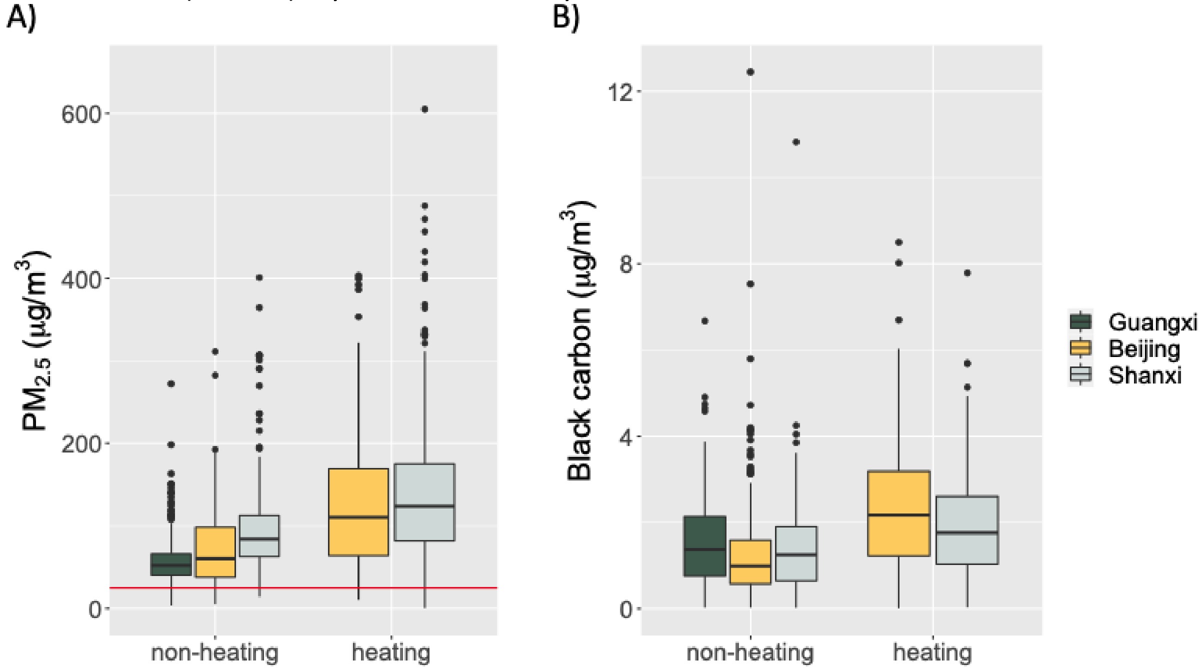
Personal exposures to $PM_{2.5}$ and black carbon

We obtained 2073 complete 24-h measurements of personal exposure to $PM_{2.5}$ (92% of attempted), of which 1291 were collected in the non-heating season and 782 in the heating season. Of the 787 study participants, 778 of the 787 participants had at least 1 complete $PM_{2.5}$ measurement and 703 had 2 complete measurements. In the northern sites with 2 seasons of measurements, 370 participants had 3 complete measurements and 223 had 4 complete measurements. Most (97%) post-sampling pump flow rates were within ±10% of the target flow rate.

Daily (24-h) exposures to $PM_{2.5}$ and black carbon ranged from 0.01-1528 and 0.00-12 μg/m^3, respectively. Overall, 92% of 24-h $PM_{2.5}$ exposure measurements were higher than the World Health Organization (WHO) guideline of 25 μg/m^3 (88% in Guangxi; 90% in Beijing; 96% in Shanxi), and 79% of exposure measurements were higher than outdoor $PM_{2.5}$ on the same day (68% in Guangxi; 74% in Beijing; 90% in Shanxi). We found low to moderate correlations between exposures to $PM_{2.5}$ and black carbon on the same day (r=0.49) and between the same pollutant on the first and second measurement days (r=0.44 for $PM_{2.5}$; r=0.40 for black carbon), with little difference by season (**Figure S5**). The correlation between daily personal exposure and outdoor air pollution concentrations from the same day was low (r = 0.33 for $PM_{2.5}$; r=0.40 for black carbon).

In the northern sites (Beijing and Shanxi), air pollution exposures were similar in the heating season but higher in Shanxi in the non-heating season (**Figure 1**). Guangxi participants had the lowest exposures to $PM_{2.5}$, however, their exposures to black carbon were similar to or higher than northern participants in the same season (**Table 1**). Air pollution exposures were higher among men (**Table 2**), though this gender difference was largely eliminated after accounting for active tobacco smoking (**Figure S6**). Participants exclusively using clean fuel for cooking, heating, or all energy use had exposures that were similar to users of solid fuel (**Table 2**).

Figure 3: Distributions of average 24-h exposures to A) $PM_{2.5}$ and B) black carbon in peri-urban Chinese adults (n = 787), by season and study site[a]



The red line indicates the World Health Organization's 24-h $PM_{2.5}$ guideline of 25 µg/m^3

[a]We averaged repeat exposure samples from the same season so that each participant only contributed one measurement per season. The y-axis for $PM_{2.5}$ was limited to 650 µg/m^3 to facilitate visual comparison, which excluded 3 observations (710, 838, and 1241 µg/m^3).

Table 2: Geometric mean [and 95% confidence intervals] personal exposures to $PM_{2.5}$ and black carbon ($\mu g/m^3$) in peri-urban Chinese adults by season, gender, and household fuel use

Exposure group	Heating season[a]			Non-heating season[a]		
	$N_{participants}$ ($N_{filters}$)	$PM_{2.5}$	Black carbon	$N_{participants}$ ($N_{filters}$)	$PM_{2.5}$	Black carbon
All participants	443 (785)	108 [100,116]	1.7 [1.6,1.8]	738 (1291)	65 [62,68]	1.1 [1.0,1.1]
Men	201 (340)	122 [110,135]	1.7 [1.5,2.0]	320 (566)	72 [67,77]	1.1 [1.0,1.2]
Women	241 (444)	98 [88,108]	1.6 [1.5,1.8]	412 (723)	61 [58,64]	1.0 [1.0,1.1]
Exclusive use of clean fuel[b] for cooking	238 (431)	101 [91,113]	1.8 [1.6,2.0]	336 (584)	64 [60,69]	1.0 [0.9,1.1]
Use of solid fuel[b] for cooking	197 (344)	113 [103,124]	1.6 [1.4,1.7]	376 (672)	67 [63,71]	1.2 [1.1,1.3]
Exclusive use of clean fuel for heating	116 (208)	108 [95,122]	1.7 [1.5,2.0]	205 (363)	67 [62,73]	1.2 [1.1,1.4]
Use of solid fuel for heating, indoor stoves	271 (482)	109 [100,119]	1.7 [1.5,1.9]	301 (522)	71 [65,76]	0.9 [0.8,1.0]
Use of solid fuel for heating, outdoor stoves	35 (60)	86 [54,137]	1.4 [1.0,1.9]	33 (55)	71 [57,88]	0.8 [0.6,1.1]
Exclusive use of clean fuel for cooking and heating	73 (134)	114 [97,133]	1.9 [1.6,2.2]	165 (286)	66 [61,72]	1.3 [1.2,1.4]
Use of solid fuel for cooking and/or heating	362 (641)	105 [97,114]	1.6 [1.5,1.8]	547 (970)	66 [62,69]	1.0 [0.9,1.1]

PM, particulate matter

[a] Heating season includes measurements from northern sites only; non-heating season includes measurements from all 3 sites. The 2 24-h measurements were averaged to estimate 'daily' within-season exposure for each participant. We used the single 24-h measurement if 2 complete measurements were not available.

[b] Clean fuel refers to gas and/or electricity and solid fuel refers to use of biomass and/or coal.

Outdoor $PM_{2.5}$

Daily outdoor $PM_{2.5}$ (from government monitors) ranged from 6 to 407 $\mu g/m^3$ (geometric mean (GM): 67) (**Figure S7**). In the heating season, Beijing and Shanxi had similar outdoor $PM_{2.5}$ (GM: 55 and 54 $\mu g/m^3$, respectively). In the non-heating season, Shanxi had the lowest outdoor $PM_{2.5}$ (GM: 22 $\mu g/m^3$ compared with 38 $\mu g/m^3$ in Guangxi and 45 $\mu g/m^3$ in Beijing). Average (GM) personal exposures were consistently higher than average outdoor $PM_{2.5}$ in the same season (+38 $\mu g/m^3$ in Beijing heating season; +49 $\mu g/m^3$ in Shanxi heating season; +17 $\mu g/m^3$ higher in Guangxi non-heating season; +17 $\mu g/m^3$ in Beijing non-heating season; and +59 $\mu g/m^3$ in Shanxi non-heating season).

Variance components of personal exposure to $PM_{2.5}$ and black carbon

In the base intercept-only models, the proportion of total variability in air pollution exposure attributed to between-individual differences was low to moderate (range of ICCs: 0.05-0.32), with consistently greater within-individual variability than between-individual variability (**Table 3**). Compared with models including all observations, the ICCs were similar for gender-specific models (range: 0.05-0.14) but higher in season-specific models (0.29-031), indicating that day-to-day measurements within the same season are more similar than measurements for the same individual in different seasons. The ranges of ICCs were similar for models predicting $PM_{2.5}$ (0.08-0.29) versus black carbon (0.07-0.32).

Table 3: Estimates of between-individual and within-individual components of variance of 24-h measurements of personal exposure to $PM_{2.5}$ and black carbon from random intercept-only models

	Models predicting $PM_{2.5}$					**Models predicting black carbon**				
	All obs	Women	Men	Heating	Non-heating	All obs	Women	Men	Heating	Non-heating
Mean ($\ln(\mu g/m^3)$); 95% CI	4.3 4.2-4.3	4.2 4.1-4.2	4.4 4.3-4.4	4.6 4.5-4.6	4.1 4.1-4.1	0.1 0.1-0.2	0.1 0.0-0.1	0.2 0.1-0.2	0.4 0.3-0.5	-0.1 -0.1-0.0
Between-individual variance (σ_b^2)	0.10	0.07	0.12	0.35	0.21	0.10	0.12	0.07	0.35	0.33

Within-individual variance (σ_{w}^2)	0.80	0.83	0.77	0.76	0.48	1.10	1.04	1.19	0.85	0.80
ICC	0.11	0.07	0.14	0.32	0.31	0.08	0.10	0.05	0.29	0.29

CI, confidence interval; ICC, intraclass correlation coefficient; obs, observations; PM, particulate matter
Note: The ICC is the proportion of total variability in exposure attributed to between-individual differences.

Model Fit and Performance

The within-individual variance remained much larger than the between-individual variance, even after including outdoor air quality and other time-varying variables in the models (σ_{w}^2 = 0.65-1.11; σ_b^2 = 0.05-0.13) (**Table 4**). Outdoor $PM_{2.5}$ explained the largest proportion of within-individual variance relative to the $PM_{2.5}$ intercept-only model (+16%). The addition of other time-varying variables including season, outdoor temperature, and relative humidity had limited additional explanatory power (+2% for $PM_{2.5}$ and +5% for black carbon). Indoor sources (smoking status and household fuel type) and study site explained the largest proportion of between-individual variability in $PM_{2.5}$, while outdoor $PM_{2.5}$ had little impact. Adding indoor sources and other time-invariant variables into the black carbon models had little impact on the explained between-individual variance. Socio-demographic variables including age, gender, occupation, marital status, education, and income had little to no explanatory power. Compared with the intercept-only models, the full models explained an additional 20% and 5% of within-individual variance and an additional 46% and 11% of between-individual variance in exposure to $PM_{2.5}$ and black carbon, respectively.

The RMSE between the natural logged-transformed predicted and measured air pollution exposures decreased as covariates were successively added into the models (from 0.86 to 0.77 for $PM_{2.5}$ and from 1.02 to 0.92 for black carbon when comparing the base and full models, respectively), indicating small increases in predictive validity (**Table 4**). We also observed small increases in the Spearman correlation (from 0.60 to 0.66 for $PM_{2.5}$ and from 0.55 to 0.60 for black carbon).

Table 4: Model prediction and fit of linear mixed effect models predicting personal exposure to $PM_{2.5}$ and black carbon (BC) in peri-urban Chinese adults

		Prediction				Fit		
		Within-individual variance (σ_e^2)	Between-individual variance (σ_b^2)	R^2_{within}[a]	$R^2_{between}$[b]	ICC *(ρ)**	RMSE	Spearman correlation
Base random intercept model $ln(Y_{ik}) = \beta_0 + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.81 1.11	0.10 0.09	Ref Ref	Ref Ref	0.11 0.07	0.86 1.02	0.60 0.55
Base + outdoor $PM_{2.5}$ $\ln(Y_{ik}) = \beta_0 + \beta_1(outdoor\ )_i + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.68 0.95	0.13 0.10	0.16 0.00	-0.32 0.00	0.16 0.10	0.78 0.94	0.66 0.62
Base + outdoor $PM_{2.5}$ + temp. + RH $\ln(Y_{ik}) = \beta_0 + \beta_1(outdoor\ )_i + \beta_2(temp.)_i + \beta_3(RH)_i + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.68 0.94	0.13 0.12	0.17 0.01	-0.36 -0.11	0.16 0.11	0.77 0.93	0.67 0.63
Base + outdoor $PM_{2.5}$ + temp. + RH + season $\ln(Y_{ik}) = \beta_0 + \beta_1(outdoor)_i + \beta_2(temp.)_i + \beta_3(RH)_i + \beta_2(season)_{ik} + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.66 0.91	0.10 0.11	0.18 0.05	-0.01 -0.06	0.13 0.11	0.77 0.91	0.65 0.64
Base + outdoor $PM_{2.5}$ + temp. + RH + season + fuel[c] $ln(Y_{ik}) = \beta_0 + \beta_1(outdoor)_i + \beta_2(temp.)_i + \beta_3(RH)_i + \beta_4(season)_i + \beta_5(fuel)_{ik} + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.66 0.91	0.09 0.10	0.19 0.05	0.07 0.05	0.12 0.10	0.77 0.91	0.65 0.61
Base + outdoor $PM_{2.5}$ + temp. + RH + season + fuel[c] + smoke $ln(Y_{ik}) = \beta_0 + \beta_1(outdoor)_i + \beta_2(temp.)_i + \beta_3(RH)_i + \beta_4(season)_i + \beta_5(fuel)_{ik} + \beta_6(smoke)_{ik} + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.66 0.91	0.06 0.09	0.19 0.05	0.35 0.10	0.09 0.09	0.78 0.92	0.64 0.61
Base + outdoor $PM_{2.5}$ + temp. + RH + season + fuel[c] + smoke + site $lln(Y_{ik}) = \beta_0 + \beta_1(outdoor)_i + \beta_2(temp.)_i + \beta_3(RH)_i + \beta_4(season)_i + \beta_5(fuel)_{ik} + \beta_6(smoke)_{ik} + \beta_7(site)_{ik} + b_i + \varepsilon_{ik}$	$PM_{2.5}$ BC	0.65 0.91	0.05 0.09	0.20 0.05	0.46 0.11	0.07 0.09	0.78 0.92	0.66 0.60
Full model: Base + outdoor $PM_{2.5}$ + temp. + RH + season + fuel[c] + smoke + site + all other covariates[d]	$PM_{2.5}$ BC	0.65 0.91	0.05 0.09	0.20 0.04	0.46 0.11	0.07 0.09	0.77 0.92	0.66 0.60

$$
\begin{aligned}
ln(Y_{ik}) = \ & \beta_0 + \beta_1(outdoor)_i + \beta_2(temp.)_i \\
& + \beta_3(RH)_i + \beta_4(season)_i \\
& + \beta_5(fuel)_{ik} + \beta_6(smoke)_{ik} \\
& + \beta_7(site)_{ik} + \beta_8(X)_{ik} + b_i + \varepsilon_{ik}
\end{aligned}
$$

PM, particulate matter; BC, black carbon; ICC, intraclass correlation; R^2, coefficient of determination; temp, temperature; RH, relative humidity

[a] Within-individual variance explained relative to the intercept-only model.

[b] Between-individual variance explained relative to the intercept-only model.

[c] Variables for cooking and heating fuel were added separately into the models.

[d] Includes participant age, gender, occupation, marital status, education, and income

We continued to observe strong seasonal and regional patterns in pollution exposures in the multivariable models (**Table 5**). Exposures to $PM_{2.5}$ and black carbon in the non-heating season were 63% lower (95% CI: -72%, -51%) and 78% lower (95% CI: -84%, -69%) than in the heating season, respectively, even after accounting for outdoor air quality, temperature, and humidity. Participants in Beijing and Shanxi had 38% and 70% higher exposure to $PM_{2.5}$ than participants in Guangxi, respectively, though the opposite trend was observed for black carbon (compared with Guangxi, black carbon exposures were 13% and 18% lower in Beijing and Shanxi, respectively).

Indoor sources including household fuel type and smoking patterns were strongly associated with exposures. Participants exclusively cooking with gas and electric stoves had 15% lower exposure to $PM_{2.5}$ and black carbon than users of solid fuel stoves. Compared with participants using solid fuel heating stoves indoors, participants with outdoor stoves had 25% lower (95% CI: -37%, -10%) exposure to $PM_{2.5}$ and 20% lower (95% CI: -35%, -0.5%) exposure to black carbon, though no differences were observed for users of clean fuel heating stoves or without heating-specific stoves. Poor outdoor air quality was associated with higher exposure [6% higher $PM_{2.5}$ (95% CI: 5%, 7%) and 8% higher black carbon (95% CI: 7%, 9%) per 10 μg/m^3 increase in outdoor $PM_{2.5}$]. Participants that were male, had lower household incomes, or that worked outside of the home had 2-14% higher exposures to air pollution, though the differences were not statistically significant.

The gender-specific models were very similar to the full models with the exception of outdoor solid fuel heating stove use which, compared with use of indoor solid fuel heating stoves, was associated with lower exposures in women (-37%; 95% CI: -51%, -20%) but not in men (**Table S3**). Season-specific models suggest that outdoor air quality may have a larger impact on exposure in the non-heating season than the heating season (10% versus 4% higher exposure per 10 μg/m^3 increase in outdoor $PM_{2.5}$). We did not observe any qualitative differences in our results after excluding observations that did not capture ±10% of the target 24-h sampling time, or when comparing results from models with measurement versus estimated outdoor $PM_{2.5}$ (**Table S4**).

Table 5: Associations between personal exposures to air pollution and selected sociodemographic, energy use, and environmental variables[a]

	Percent (%) change in $PM_{2.5}$ based on log regression* (95% CI) (n = 2022 filters)	**Percent (%) change in black carbon based on log regression* (95% CI) (n = 2026 filters)**
Age, per year	-0.2 [-0.8,0.4]	0.0 [-0.7, 0.8]
Gender		
male (ref: female)	4.6 [-6.1, 16.5]	6.5 [-6.5, 21.4]
Occupation		
agriculture (ref)		
other work outside the home	5.9 [-10.3, 24.9]	14.1 [-6.6, 39.3]
not working outside the home	-3.2 [-13.1, 7.8]	-6.1 [-17.6, 7.0]
Annual household income (yuan)		
<20000 (ref: ≥20000)	3.1 [-5.9, 13.0]	1.6 [-9.1, 13.6]
Education		
college/high (ref)		
primary	0.4 [-8.7, 10.5]	4.5 [-6.9, 17.3]
no school	-5.4 [-17.2, 8.1]	7.2 [-8.8, 26.1]
Smoking status		
smoker (ref)		
non-smoker w/ household	-26.2 [-36.3, -14.4]***	-1.3 [-17.5, 8.2]
smoker	-30.4 [-38.0, -21.8]***	-12.8 [-24.2, 0.3]*
non-smoker w/o household smoker		
Cooking fuel		
clean fuel use (ref: any solid fuel)	-15.4 [-22.3, -8.0]***	-14.8 [-23.1, -5.6]***
Heating fuel		
indoor solid fuel (ref)		
outdoor solid fuel use	-24.6 [-36.98, -9.8]***	-19.9 [-35.0, -0.5]**
only clean fuel	-2.8 [-12.3, 7.7]	5.6 [-6.7, 19.6]
no devices	-1.6 [-16.6, 16.3]	2.1 [-16.5, 24.8]
Season		
non-heating (ref: heating)	-62.8 [-71.8, -50.9]***	-78.0 [-84.2, -69.3]***
Outdoor $PM_{2.5}$, per 10 µg/m³	5.8 [4.7, 6.9]***	7.9 [6.6, 9.2]***
Ambient RH, per 1%	0.8 [0.5, 1.1]***	0.0 [-0.3, 0.4]
Ambient temperature, per 1°C	3.4 [2.2, 4.6]***	5.5 [4.1, 7.0]***
Site		
Guangxi (ref)		
Beijing	37.9 [15.0, 65.3]***	-12.8 [30.0, 8.5]
Shanxi	69.9 [43.1, 101.6]***	-18.4 [-33.7, 0.3]*
Marginal R^2	0.24	0.17
Conditional R^2	0.29	0.24

*p-value <0.10; **p-value <0.05; ***p-value<0.001; obs, observations

[a] Regression of log-air pollution exposure can be converted to the percent (%) change in exposure using the equation ($[\exp^{\beta} - 1] \times 100$), where β is the change in log-transformed pollution exposure associated with a one-unit change in the independent variable.

Discussion

We conducted one of the largest and most comprehensive household air pollution exposure studies to date, which included over 2073 measurements of 24-h personal exposures to $PM_{2.5}$ and black carbon from 778 participants. By conducting repeated measurements across seasons, we were able to describe the levels and variability in $PM_{2.5}$ exposures in peri-urban men and women living in 3 diverse provinces of China and also assess the explanatory contribution of indoor and outdoor sources to variability and levels of personal exposures.

Personal exposures to $PM_{2.5}$ in our study were within the range of exposures observed among non-smoking women cooking with biomass stoves in southwestern China (range of GMs: 47-91 μg/m^3 in summer and 107-201 μg/m^3 in winter)(10, 159, 161) but were higher than exposures among urban Chinese (range of means: 33-93 μg/m^3)(168-170). Outdoor $PM_{2.5}$ was high in our study settings, exceeding the WHO's 24-h Air Quality Guideline on 56% of study measurement days. Though our finding that personal exposures were consistently higher than outdoor air pollution, particularly in northern China, highlights the contribution of indoor sources to exposures in settings with poor outdoor air quality.

Large and consistent differences in outdoor air quality and exposures were observed by geographic region. Of our 3 study sites, Guangxi participants (southern China) had the lowest exposures to $PM_{2.5}$ in the non-heating season but the highest exposures to black carbon. This result may be in part due to the higher proportion of Guangxi participants exclusively using clean fuel stoves (31% versus 19% in the northern sites) and their more common use of biomass stoves which can emit proportionally higher levels of black carbon compared with coal stoves (171, 172). Guangxi participants also lived in homes that were closer to major roadways (3-11 km) and secondary roads, which may also have influenced their exposures to black carbon

(173, 174). Planned chemical analysis of a sub-sample of PTFE filters from the study will provide a better understanding of the source-specific contributors to exposures in our study.

In northern China, air pollution exposures were twice as high in the heating season than the non-heating season, a result that is likely in part attributable to space heating stove emissions and potentially due to less time spent outside the home. The role of these very high seasonal exposures on health, particularly for cardiovascular diseases, should be further investigated. Seasonal variability of cardiovascular diseases is well-documented in China and elsewhere, showing mostly a peak in winter months (175, 176). The exact causes of these seasonal differences are not fully understood, though environmental factors like air pollution are strongly associated with cardiovascular outcomes and thus may play some role (175). Replacing traditional coal and biomass space heating stoves with electric or gas appliances may therefore benefit both outdoor and indoor air quality and population health in northern China (141).

Both active smoking and environmental tobacco smoke were important contributors to exposure, with the former impacting men and the latter impacting women. Men in our study had higher exposures than women, on average, though exposures among non-smoking women and men were similar. Policy organizations including the WHO consistently highlight the high levels of household air pollution exposures among women and children (177), but very few studies have measured exposure in men (7, 178, 179). The gender-specific results from our study align with measurements of $PM_{2.5}$ exposure in largely non-smoking men in peri-urban India, which were similar to women (55 versus 58 $\mu g/m^3$). By comparison, women in a small exposure study conducted in rural Ethiopia and Uganda had exposures to $PM_{2.5}$ that were 5-6 times higher than men in the same villages. Women in our study sites were usually the primary cooks, though men can be in close proximity to cooking stoves even if they are not cooking themselves. Men also participated in other household energy tasks. For example, men were often responsible for operating space heating stoves where they can be episodically exposed to high levels of pollution during fuel loading. This practice is reflected in our gender-specific models, where use of an outdoor solid fuel heating stove (compared with an indoor solid fuel stove) was associated with proportionally lower exposure in women (-37%; 95% CI: -51, -20) than in men (-10%; 95% CI:-31, -18), likely because men were still highly exposed to outdoor stove emissions during re-fueling.

Participants living in homes without smokers had considerably lower exposures than smokers (30% lower for $PM_{2.5}$ and 13% lower black carbon). The proportionally larger difference for $PM_{2.5}$ may be due to the large organic fraction in tobacco smoke (180) which contributes to higher $PM_{2.5}$ but not higher black carbon. A somewhat surprising finding in the crude (unadjusted) analysis was that participants in homes exclusively cooking or heating with clean fuel stoves still had high exposures to $PM_{2.5}$ (GM: 76 $\mu g/m^3$; range: 11 – 392 $\mu g/m^3$) that were similar to participants using solid fuel stoves (GM: 81 $\mu g/m^3$; range: 3 – 838 $\mu g/m^3$). After statistically accounting for outdoor air quality and other variables, exclusive users of clean fuel cookstoves and heating stoves had only modestly lower exposures than indoor solid fuel users (-3 to -15% for $PM_{2.5}$). These results provide further empirical evidence that poor outdoor air quality and other behavioral factors can mask the benefit of clean energy use, but also highlight the importance of evaluating all major sources of air pollution in intervention studies to better understand their relative contributions to exposures and also have more realistic expectations of the air pollution exposure benefits of a clean stove intervention in settings where other sources are also present.

We observed high within-individual variability in 24-h exposure across seasons and within the same season, particularly when compared with between-individual variance. Based on our mixed-effects models, we partly attribute this finding to the high day-to-day variability in outdoor air quality, though a large portion of within-individual variance remained unexplained in the full models. The ICCs in our base and covariate-adjusted models ($PM_{2.5}$: 0.11-0.16; black carbon: 0.08-0.11) were lower than those observed for carbon monoxide exposure among children in The Gambia (ICC=0.33)(181), but overlapped with those among adults in Guatemala (carbon monoxide ICC: 0.11-0.33)(8) and peri-urban India ($PM_{2.5}$ ICC: 0.0-0.22)(11). As expected, the ICCs in our study were higher in the season-specific models, but still indicated poor reliability (range: 0.29-0.32). Overall, our results indicate that a single day of measured exposure is not likely representative of longer-term exposure, which is the exposure metric most relevant for many chronic health outcomes including cardiovascular diseases (66, 117). They also highlight the challenges of identifying the impact of any given source on personal exposure in these complex air pollution settings where behaviors like time spent in different locations or doing certain activities are likely important determinants of exposure that are not easily captured by traditional survey methods and measurements (182).

Notable strengths of this study include the comprehensive dataset of over 48,000 hours of personal exposure monitoring in 3 diverse provinces of China which includes measurements of exposure among men and exclusive clean fuel users in villages using solid fuel energy. Despite the considerable practical and logistical challenges of conducting large panel studies of exposure in these settings (183), we were able to obtain at least 2 days of measured air pollution exposures for 90% of participants and 4 days for 60% of northern China participants, which allowed us to evaluate the within-individual and between-individual variance in daily exposure. These results contribute to the very limited evidence on representativeness of short-term measurement of exposure for longer-term exposure estimation in field studies of household air pollution. Further, the additional assessment of very detailed energy use and outdoor $PM_{2.5}$ allowed us to evaluate the influence of indoor versus outdoor sources to personal exposures, which are contributions to exposures that remain poorly understood in many settings, especially relative to one another.

Our study is not without limitations. Though we achieved high compliance in wearing the air monitors (98% in participants randomly selected for compliance monitoring with a pedometer), it is possible that some participants altered their daily activity patterns while wearing them. We also cannot rule out the possibility that wearing the monitors or visiting the clinics may have changed participants' behaviors. We were unable to account for time-varying behaviors which are likely important determinants of exposure in our study participants such as stove use on the measurement days or time-activity patterns. Combined use of GPS monitors or Bluetooth signal receivers can track participant location during measurement and allow investigators to better assess activity patterns in field studies(184), though the required data processing and analysis can be time-intensive in large studies like this one. We were limited to 2 days of measurement per season due to study logistics and participant burden in wearing the monitors, which limited our ability to assess 'long-term" exposure over weeks or months. The recent development of quiet and less bulky $PM_{2.5}$ monitors may ease some of the logistical and participant burdens of longer-term measurements. In addition to the detailed fuel and stove use data collection in this study, future studies could also collect information on home ventilation which was not collected in this study.

Conclusion

Personal exposures to $PM_{2.5}$ across all seasons and study sites were, on average, higher than the WHO's 24-h $PM_{2.5}$ air quality guideline and higher than the relatively high levels of outdoor $PM_{2.5}$. Our repeated measures show that within-individual variance dominated the total variability in personal exposures across all study sites, genders, and seasons. Repeated daily measurements of exposure are thus needed to capture 'usual' daily exposure for epidemiological and intervention studies in these settings, even within a single season. Our results also indicate that measurably reducing air pollution exposures in these study settings will likely require reductions in emissions from both indoor and outdoor air pollution, which are linked to different air pollution mitigation policies and interventions.

Acknowledgements

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3.3 Supplementary Material

Figure S1: Location of study sites in the INTERMAP China Prospective (ICP) Study

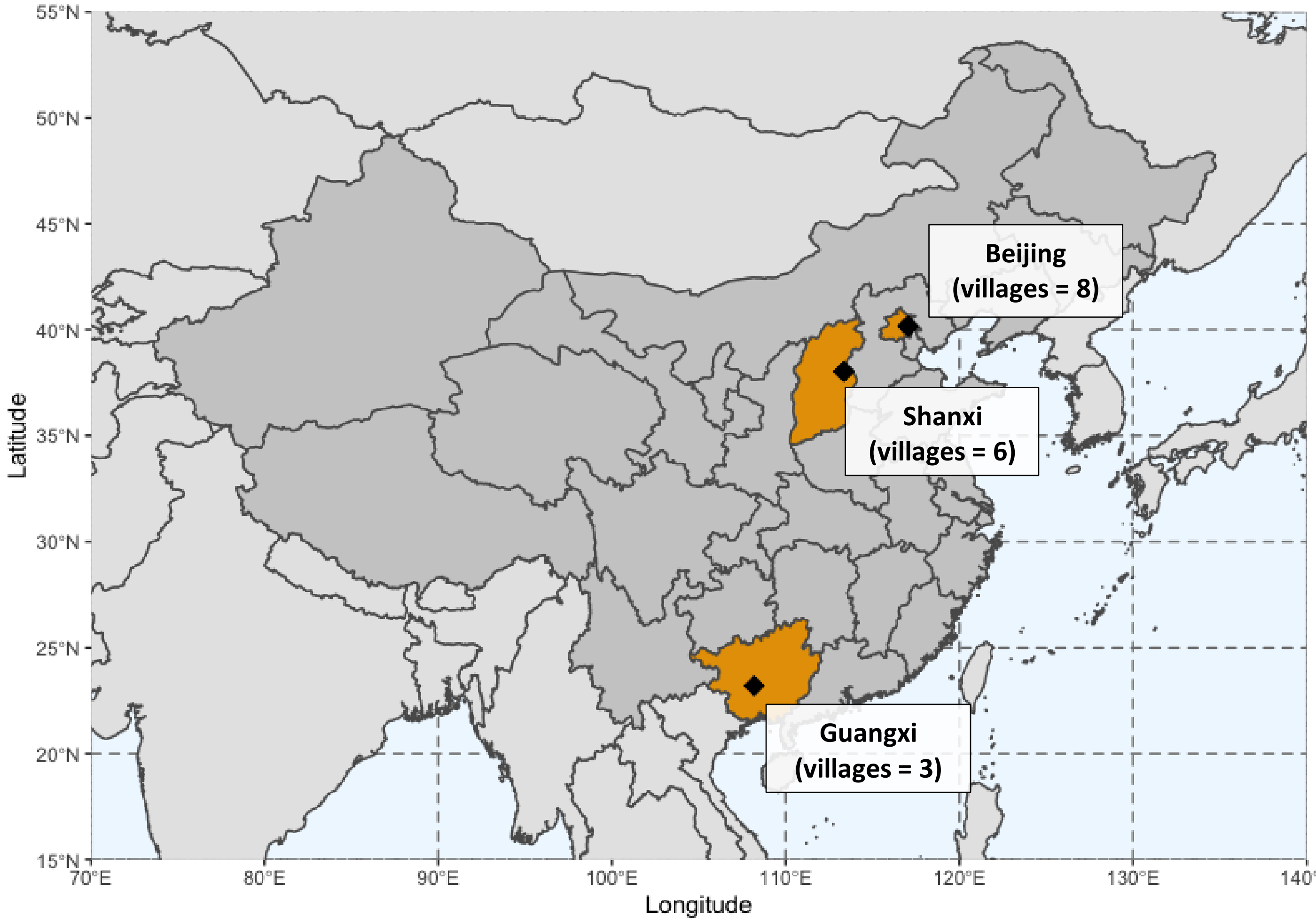


Figure S2: Setup of the Harvard Personal Exposure Monitor within waistpacks (Photo credit: Ellison Carter)

Figure S3: Scatterplot of outdoor 24-h average $PM_{2.5}$ estimated from government monitors using inverse distance weighting versus measured outdoor $PM_{2.5}$ collected in the study villages

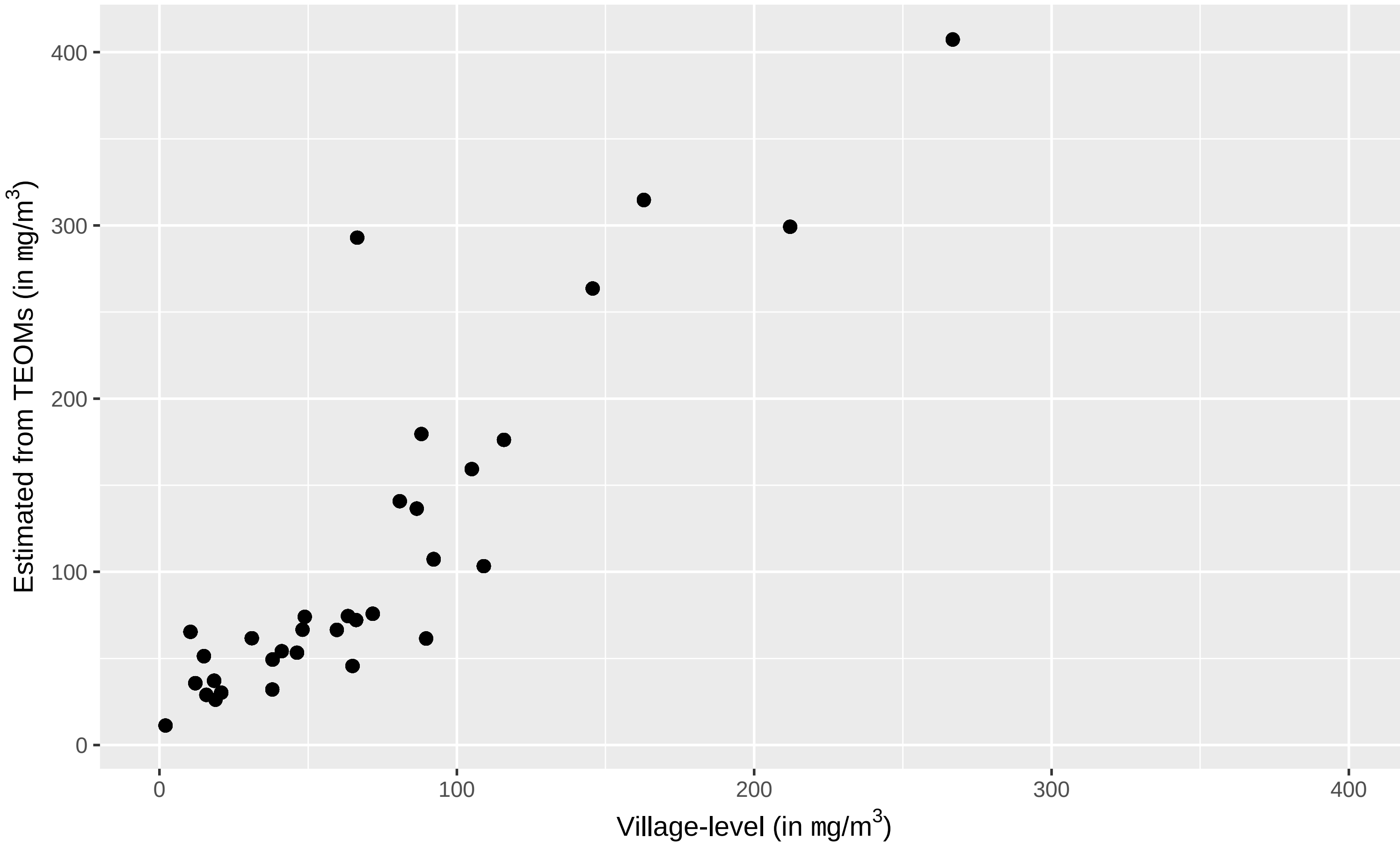


Figure S4: Scatterplot of outdoor 24-h average temperature estimated from government monitors using inverse distance weighting versus measured outdoor temperatures in centrally-located clinics in each study village

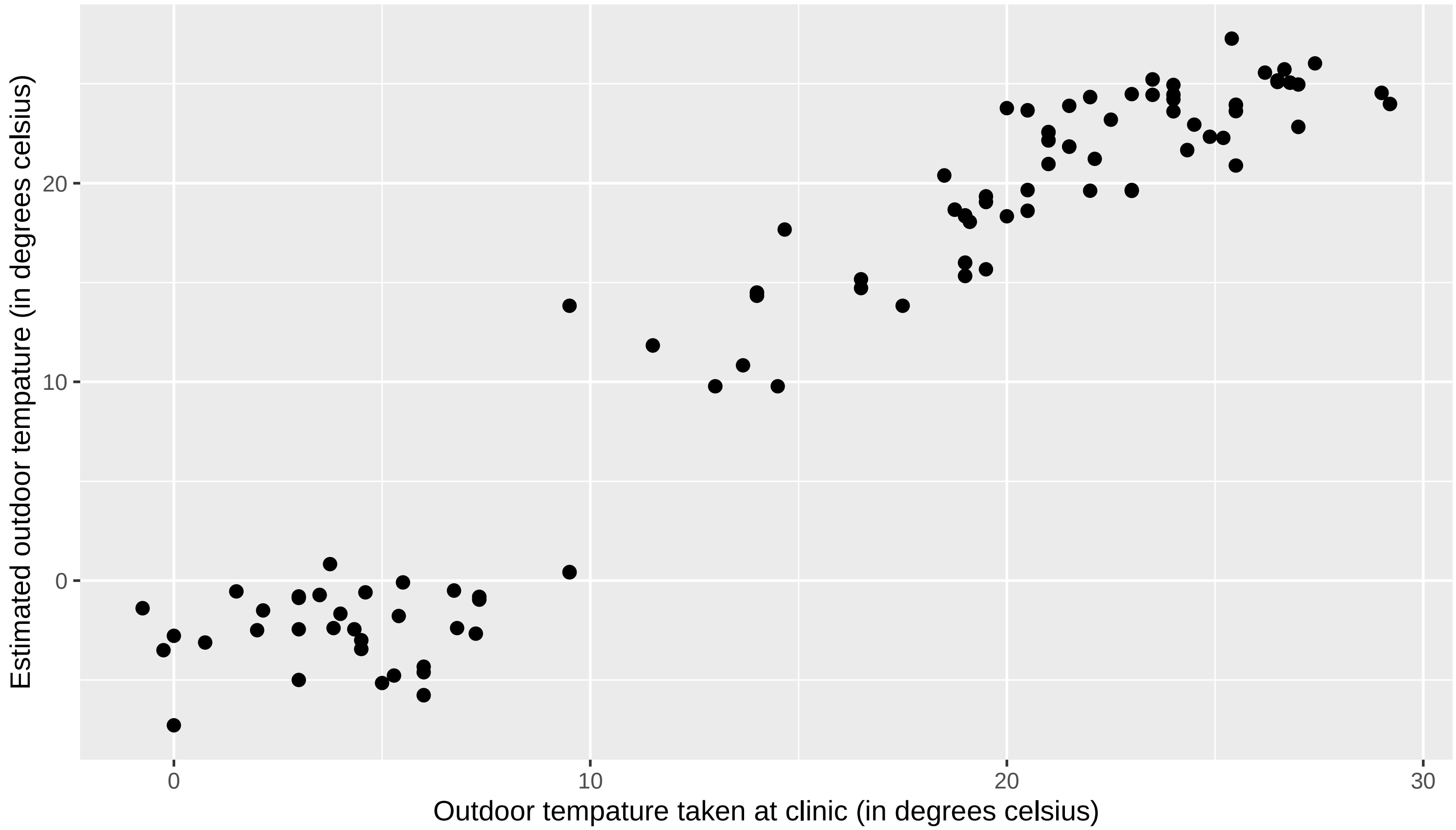


Figure S5: Pearson correlations between (A) exposures to $PM_{2.5}$ and black carbon (BC) on the same day for all participants and between (B) $PM_{2.5}$ and (C) black carbon exposures on subsequent sampling days for the same participants

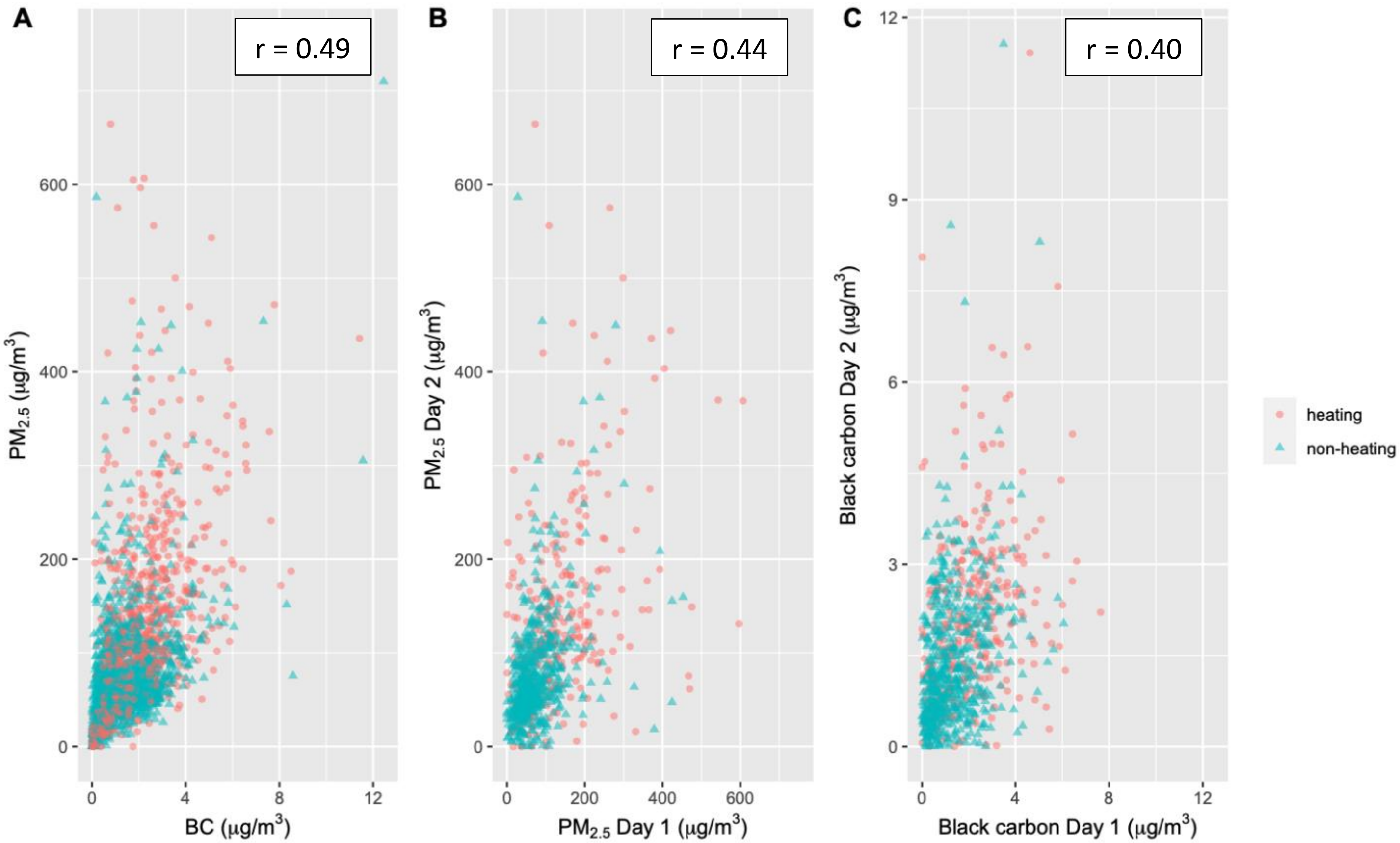
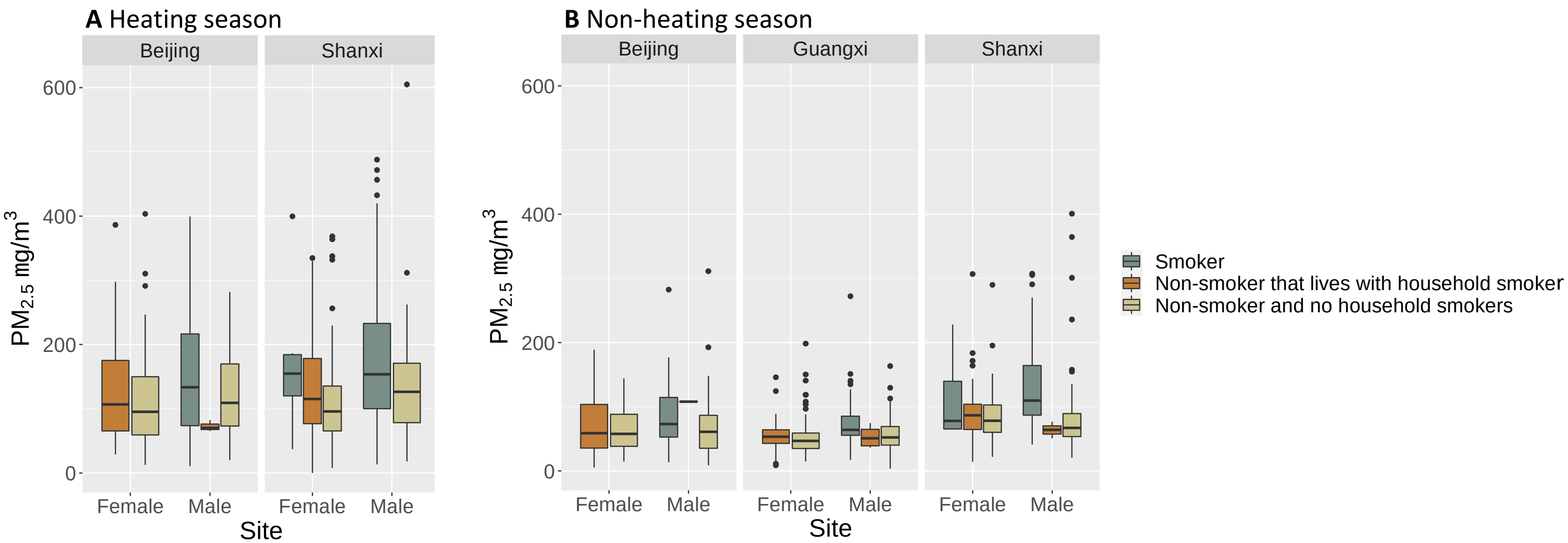
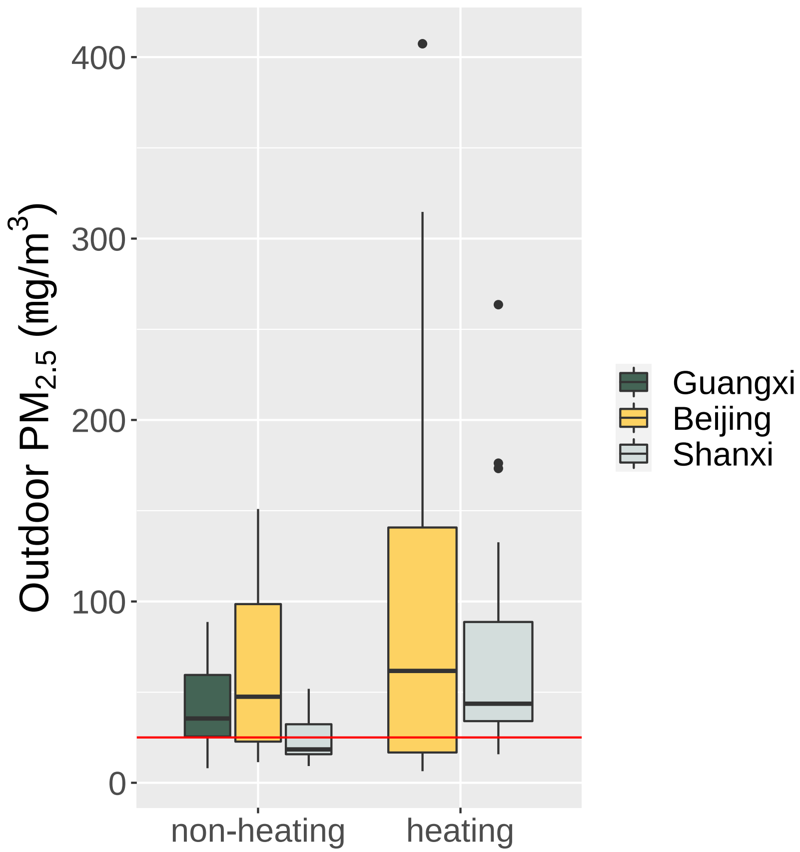


Figure S6: Personal exposure to $PM_{2.5}$ by study site and gender in the heating (A) and non-heating (B) seasons



Personal exposures consisted of at least one observation per participant, but if the participant had two measurements from that season, they were both averaged. To facilitate better visual comparison of the data, this Figure excludes one high exposure observation from the heating season (838 $\mu g/m^3$ – a male non-smoker with no household smokers from Shanxi) and two high exposure observations from the non-heating season (710 $\mu g/m^3$ – a male non-smoker with no household smokers from Beijing and 1241 $\mu g/m^3$ – a male smoker from Shanxi).

Figure S7. Distributions of average 24-h outdoor $PM_{2.5}$ (estimated from government monitors) in the heating and non-heating seasons at our study sites



Note: The red line indicates the World Health Organization 24-h guideline for outdoor $PM_{2.5}$ at the time of publication (25 μg/m^3) (64)

Table S1: Personal exposures to $PM_{2.5}$ and black carbon (BC) in peri-urban Chinese adults by socio-demographic and energy use variables (geometric means [95% CI]) in μg/m^3)

	Guangxi		**Beijing**				**Shanxi**			
	Non-heating		**Non-heating**		**Heating**		**Non-heating**		**Heating**	
	$PM_{2.5}$	**BC**	**$PM_{2.5}$**	**BC**	**$PM_{2.5}$**	**BC**	**$PM_{2.5}$**	**BC**	**$PM_{2.5}$**	**BC**
# of participants (# of filters)	238 (442)	238 (441)	228 (383)	228 (384)	237 (432)	237 (433)	269 (467)	270 (468)	205 (350)	206 (352)
All samples	51[48, 55]	1.2 [1.1,1.3]	59.4 [54,65]	1.0 [0.9,1.1]	103 [94,112]	1.8 [1.6,2.0]	88 [82,94]	1.0 [0.9,1.1]	114 [101,128]	1.6 [1.4,1.74]
Age										
40 – 49	59 [50,69]	1.2 [0.9,1.5]	54 [31,95]	0.7 [0.2,2.8]	70 [53,92]	1.9 [1.3,2.6]	79 [66,94]	0.7 [0.4,1.0]	66 [32,138]	1.4 [0.9,2.4]
50 – 59	51 [44,60]	1.1 [0.9,1.5]	71 [59,84]	1.1 [0.9,1.4]	72 [61,86]	1.3 [1.1,1.6]	97 [84,111]	1.0 [0.9,1.3]	129 [110,151]	1.8 [1.6,2.2]
60 – 69	51 [46,57]	1.2 [1.1,1.4]	55 [49,63]	0.8 [0.7,1.0]	122 [107,139]	1.9 [1.6,2.3]	88 [80,97]	1.1 [1.0,1.3]	118 [101,137]	1.5 [1.3,1.8]
70 – 79	49 [42,56]	1.3 [1.0,1.6]	57 [47,68]	1.0 [0.8,1.2]	128 [108,153]	2.3 [1.9,2.8]	81 [72,90]	1.1 [0.9,1.3]	118 [92,151]	1.4 [1.1,1.8]
Gender										
male	56 [50,62]	1.4 [1.2,1.6]	67 [58,77]	1.0 [0.8,1.2]	110 [95,128]	1.7 [1.4,2.1]	95 [85,107]	1.0 [0.8,1.2]	135 [117,157]	1.8 [1.6,2.1]
female	48 [44,52]	1.1 [1.0,1.3]	55 [49,61]	0.9 [0.8,1.1]	98 [87,110]	1.9 [1.7,2.1]	82 [77,88]	1.1 [1.0,1.2]	97 [82,116]	1.4 [1.2,1.6]
Ethnicity										
Han	49 [44,54]	1.2 [1.0,1.4]	60 [55,65]	1.0 [0.9,1.1]	103 [94,113]	1.8 [1.6,2.0]	88 [82,94]	1.0 [0.9,1.1]	114 [101,128]	1.6 [1.4,1.7]
Zhuang	54 [49,60]	1.3 [1.1,1.5]	-	-	-	-	-	-	-	-
other	-	-	33 [14,78]	0.5 [0.0,23.5]	105 [100,109]	1.6 [0.0,387]	-	-	-	-
Current occupation										
agriculture	55 [50,61]	1.4 [1.2,1.7]	60 [54,66]	1.0 [0.9,1.1]	100 [90,111]	1.7 [1.5,2.0]	87 [82,94]	1.1 [0.9,1.2]	118 [102,136]	1.6 [1.4,1.8]
other work outside the home	58 [46,73]	1.2 [0.8,1.7]	70 [48,102]	0.9 [0.5,1.8]	110 [82,147]	1.9 [1.2,3.1]	133 [90,198]	1.6 [1.1,2.5]	122 [76,193]	1.9 [1.3,2.8]
not working outside the home	49 [46,54]	1.2 [1.0,1.3]	55 [42,72]	0.9 [0.7,1.2]	122 [99,152]	2.3 [1.8,3.0]	79 [68,91]	0.8 [0.6,1.1]	99 [79,122]	1.4 [1.2,1.7]
Household income										
<20000 RMB	52 [48,56]	1.2 [1.1,1.4]	62 [54,71]	1.1 [0.9,1.3]	97 [85,110]	1.8 [1.5,2.0]	87 [78,97]	0.9 [0.8,1.1]	101 [83,122]	1.3 [1.1,1.6]
≥20000 RMB	48 [41,57]	1.1 [0.9,1.5]	58 [51,65]	0.9 [0.7,1.0]	110 [96,124]	1.8 [1.5,2.2]	88 [82,95]	1.1 [1.0,1.2]	120 [104,140]	1.7 [1.5,1.9]
Highest education attained										
no formal education	47 [38,59]	1.1 [1.0,1.4]	49 [40,59]	0.9 [0.8,1.1]	112 [95,131]	1.7 [1.5,2.0]	87 [70,107]	0.9 [0.7,1.0]	111 [82,148]	1.7 [1.4,2.0]
primary school	51 [46,56]	1.2 [0.9,1.6]	62 [53,72]	0.9 [0.7,1.1]	116 [97,138]	2.1 [1.7,2.6]	88 [80,96]	1.3 [1.0,1.7]	114 [98,132]	1.6 [1.2,2.2]
early high school	53 [48,59]	1.3 [1.1,1.5]	64 [56,74]	1.0 [0.8,1.2]	91 [79,104]	1.8 [1.4,2.2]	88 [80,97]	1.1 [1.0,1.3]	114 [91,142]	1.5 [1.3,1.7]

or college										
Smoke										
current smoker	68 [58,80]	1.6 [1.3,2.0]	74 [62,88]	1.0 [0.8,1.3]	119 [95,148]	1.6 [1.1,2.2]	118 [103,135]	1.1 [0.9,1.4]	155 [128,187]	1.9 [1.5,2.3]
not current w/ household smoker	49 [43,56]	1.1 [1.0,1.4]	57 [47,69]	1.1 [0.9,1.3]	104 [89,120]	2.1 [1.8,2.4]	83 [75,92]	1.1 [0.9,1.3]	100 [72,140]	1.5 [1.1,1.9]
not current w/o household smoker	48 [44,53]	1.2 [1.0,1.3]	56 [50,63]	0.9 [0.8,1.0]	95 [83,109]	1.7 [1.5,2.0]	77 [71,84]	1.0 [0.8,1.1]	99 [86,114]	1.5 [1.3,1.7]
Cooking fuel										
exclusive clean	53 [47, 60]	1.3 [1.1, 1.5]	57 [51, 64]	0.9 [0.8, 1.1]	93 [82, 105]	1.7 [1.4, 1.9]	84 [76, 92]	0.9 [0.7, 1.0]	118 [95, 146]	1.9 [1.6, 2.2]
solid fuel	51 [47, 56]	1.2 [1.1, 1.4]	63 [55, 73]	1.0 [0.9, 1.2]	119 [105, 135]	2.0 [1.7, 2.3]	91 [84, 100]	1.2 [1.0, 1.3]	109 [95, 124]	1.3 [1.2, 1.5]
Heating fuel										
no device	53 [48, 58]	1.2 [1.1, 1.4]	82 [30,222]	1.2[0.1, 10.1]	70 [-,-]	0.6 [-,-]	94 [70, 125]	1.6 [1.1, 2.4]	116 [74,184]	1.7 [1.2, 2.5]
exclusive clean	49 [44, 55]	1.3 [1.1, 1.5]	69 [57, 83]	1.2 [1.0, 1.4]	100 [85, 118]	1.8 [1.5, 2.1]	86 [78, 95]	1.3 [1.1, 1.5]	115 [95, 139]	1.6 [1.3, 2.0]
solid fuel (indoor)	-	-	56 [50, 63]	0.9 [0.8, 1.0]	102 [90, 114]	1.7 [1.5, 2.0]	90 [82, 98]	0.9 [0.8, 1.1]	121 [107, 137]	1.6 [1.4, 1.9]
solid fuel (only outdoor)	-	-	58 [36, 94]	1.1 [0.7, 1.6]	108 [78, 150]	2.3 [1.5, 3.8]	77 [39,152]	0.7 [0.4, 1.1]	78 [60, 100]	1.1 [0.7, 1.7]
Outdoor $PM_{2.5}$										
0-49 $\mu g/m^3$	44 [41,47]	1.0 [0.8,1.1]	36 [31,42]	0.6 [0.5,0.7]	63 [57,70]	1.1 [0.9,1.2]	83 [78,88]	0.9 [0.9,1.0]	78 [66,93]	1.0 [0.9,1.2]
50-99 $\mu g/m^3$	56 [50,64]	1.2 [1.0,1.4]	76 [68,84]	1.3 [1.1,1.5]	147 [130,165]	2.5 [2.3,2.8]	113 [87,147]	2.2 [1.7,2.8]	-	-
100-149 $\mu g/m^3$	-	-	96 [85,108]	1.1 [0.8,1.5]	159 [140,180]	3.1 [2.7,3.5]	-	-	147 [121,179]	2.4 [2.1,2.7]
> 150 $\mu g/m^3$	-	-	132 [114,153]	1.9 [1.1,3.5]	214 [192,237]	3.0 [2.2,4.1]	-	-	125 [101,155]	2.3 [2.1,2.7]

Table S2: Comparison of outdoor $PM_{2.5}$ ($\mu g/m^3$) measured by village monitors and estimated from data provided by nearly government monitoring stations, averaged across study sites

		$N_{filters}$	Heating season	Non-heating season
Outdoor				
$PM_{2.5}$ (estimated from nearby government monitors)[a]	Mean [95% CI]	NA	93 [62,124]	42 [35,50]
	Geo Mean [95% CI]		55 [39,76]	33 [28,39]
	Range		6 – 407	8 – 151
$PM_{2.5}$ (village measurement)[b]	Mean [95% CI]	33	76 [48,105]	58 [42,73]
	Geo Mean [95% CI]		47 [29,77]	54 [39,75]
	Range		2 – 267	21 – 90

Geo mean, geometric mean; PM=particulate matter

[a] Estimated from daily outdoor $PM_{2.5}$ measurements obtained from nearby government air monitoring stations. The heating season includes measurements from northern sites only, while the non-heating season includes measurements from all 3 sites

[b] Filter-based measurements of village $PM_{2.5}$ were collected during 1 season at each study site. In the heating season, village measurements were collected in Beijing and Shanxi. In the non-heating season, samples were collected in Guangxi.

Table S3: Associations between personal $PM_{2.5}$ exposure and selected sociodemographic, energy use, and environmental variables by gender and season, expressed as % change in exposure [95% CI][a]

	All Participants	**Females**	**Males**	**Heating season**	**Non-heating season**
$N_{participants}$ ($N_{filters}$)	**746 (2022)**	**413 (1137)**	**885 (333)**	**771 (433)**	**1251(709)**
Age, per year	-0.2 [-0.8,0.4]	-0.1 [-0.9, 0.7]	-0.4 [-1.3, 0.5]	0.6 [-0.5, 1.8]	-0.4 [-1.1, 0.2]
Gender					
male (ref: female)	4.6 [-6.1, 16.5]	-	-	16.2 [-5.0, 42.0]	-1.3 [-12.2, 10.9]
Occupation					
agriculture (ref)					
other work outside the	5.9 [-10.3, 24.9]	-12.3 [-35.6, 19.4]	11.7 [-9.4, 37.6]	15.6 [-16.1, 59.2]	-2.5 [-18.5, 16.6]
home	-3.2 [-13.1, 7.8]	-7.0 [-18.2, 5.9]	0.3 [-18.4, 23.4]	-4.0 [-21.0, 16.7]	-4.0 [-14.9, 8.1]
not working outside the home					
Annual household income (yuan)					
<20000 (ref: ≥20000)	3.1 [-5.9, 13.0]	4.2 [-7.5, 17.3]	0.0 [-13.9, 16.1]	4.7 [-10.4, 22.2]	6.0 [-4.6, 17.7]
Education					
college/high (ref)					
primary	0.4 [-8.7, 10.5]	-5.4 [-17.7, 8.8]	7.9 [-5.9, 23.7]	-2.5 [-17.9, 15.8]	3.3 [-7.0, 14.8]
no school	-5.4 [-17.2, 8.1]	7.6 [-21.7, 9.0]	-6.3 [-29.0, 23.6]	-6.9 [-25.7, 16.7]	-3.5 [-17.2, 12.3]
Smoking status					
smoker (ref)					
non-smoker w/ household smoker	-26.2 [-36.3, -14.4]***	-24.7 [-49.2, 11.6]	-33.6 [-54.3, -3.4]**	-16.3 [-36.1, 9.6]	-30.5 [-41.0, -18.2]***
non-smoker w/o household smoker	-30.4 [-38.0, -21.8]***	-30.0 [-52.6, 3.2]*	-29.2 [-37.7, -19.6]***	-30.3 [-43.2, -14.5]***	-29.0 [-37.6, -19.2]***
Cooking fuel					
clean fuel use (ref: solid fuel)	-15.4 [-22.3, -8.0]***	-12.7 [-22.1, -2.1]**	-19.0 [-28.9, -7.8]***	-17.4 [-29.2, -3.6]**	-11.3 [-19.2, -2.7]**
Heating fuel					
indoor solid fuel (ref)					
outdoor solid fuel use	-24.6 [-36.9, -9.8]***	-37.3 [-51.1, -19.6]***	-9.9 [-31.0, 17.7]	-37.8 [-52.7, -18.0]***	-
only clean fuel	-2.8 [-12.3, 7.7]	-8.1 [-19.5, 4.9]	5.0 [-11.1, 24.0]	-8.1 [-22.1, 8.4]	
no devices	-1.6 [-16.6, 16.3]	0.6 [-19.0, 24.9]	3.7 [-26.1, 25.3]	0.7 [-33.5, 52.4]	
Season					
non-heating (ref: heating)	-62.8 [-71.8, -50.9]***	-67.7 [-77.6, -53.5]***	-55.0 [-71.0, -30.3]***	-	-
Outdoor concentrations	5.8 [4.7, 6.9]***	6.0 [4.6, 7.4]***	5.5 [3.8, 7.1]***	3.5 [2.0, 5.1]***	9.8 [8.0, 11.6]***

per 10 $\mu g/m^3$*					
Ambient relative humidity, per %	0.8 [0.5, 1.1]***	0.8 [0.4, 1.2]***	0.7 [0.3, 1.1]***	1.5 [1.1, 2.0]***	0.8 [0.3, 1.2]***
Ambient temperature, per °C	3.4 [2.2, 4.6]***	4.3 [2.7, 5.9]***	2.1 [0.3, 4.0]**	6.0 [3.1, 8.9]***	1.9 [0.7, 3.1]***
Site					
Guangxi (ref)					
Beijing	37.9 [15.0, 65.3]***	45.1 [14.3, 84.2]***	26.8 [-4.9, 69.2]	(ref)	5.5 [-8.8, 22.1]
Shanxi	69.9 [43.1, 101.6]***	71.8 [36.7, 115.9]***	65.7 [26.7, 116.7]***	-25.6 [-37.5, -11.5]***	120.9 [89.3, 157.7]***
Marginal R^2	0.24	0.23	0.25	0.25	0.25
Conditional R^2	0.29	0.29	0.33	0.38	0.35

*p-value <0.10; **p-value <0.05; ***p-value<0.001

[a] Regression of log-air pollution exposure can be converted to the percent (%) change in exposure using the equation ($[\exp^{\beta} – 1] \times 100$), where β is the change in log-transformed pollution exposure associated with a one-unit change in the independent variable.

Table S4: Sensitivity analysis of associations between personal $PM_{2.5}$ exposure and selected sociodemographic, energy use, and environmental variables, expressed as % change in exposure [95% CI][a]

	Main analysis $PM_{2.5}$ model (all observations)	**(1) Analysis limited to $PM_{2.5}$ exposure samples within ±10% of 24-h target**	**(2) Analysis limited to $PM_{2.5}$ exposure samples that could be matched with village-level outdoor $PM_{2.5}$ measurements (village-level outdoor $PM_{2.5}$)**	**(3) Analysis limited to $PM_{2.5}$ exposure samples that could be matched with village-level outdoor $PM_{2.5}$ measurements (Outdoor $PM_{2.5}$ estimated from government monitors)**	**(4) Analysis limited to $PM_{2.5}$ exposure samples with no potentially non-compliant samples (<500 steps)**
$N_{participants}$ ($N_{filters}$)	**746 (2022)**	**744 (1913)**	**418 (606)**	**418 (606)**	**742 (1978)**
Age per year	-0.2 [-0.8,0.4]	0.0 [-0.6, 0.6]	0.1 [-0.9, 1.2]	0.2 [-0.9, 1.3]	-0.2 [-0.8, 0.4]
Gender					
male (ref: female)	4.6 [-6.1, 16.5]	3.3 [-7.2, 15.0]	21.4 [-0.5, 48.2]*	19.8 [-1.7, 46.0]*	5.6 [-5.2, 17.6]
Occupation					
agriculture (ref)					
other work outside the home	5.9 [-10.3, 24.9]	7.6 [-8.6, 26.8]	-7.1 [-28,1, 20.0]	-7.5 [-28.2, 19.3]	7.4 [-8.9, 26.8]
not working outside the home	-3.2 [-13.1, 7.8]	-4.6 [-14.4, 6.2]	-1.0 [-17.8, 19.2]	-2.8 [-19.1, 16.9]	-1.3 [-11.4, 10]
Annual household income (yuan)					
<20000 (ref: ≥20000)	3.1 [-5.9, 13.0]	2.3 [-6.6, 12.1]	-0.5 [-15.2, 16.8]	-1.5 [-16.0, 15.4]	3.4 [-5.6, 13.4]
Education					
college/high (ref)					
primary	0.4 [-8.7, 10.5]	0.5 [-8.6, 10.5]	-8.0 [-22.6, 9.3]	-8.8 [-23.2, 8.3]	2.0 [-7.3, 12.1]
no school	-5.4 [-17.2, 8.1]	-6.2 [-17.7, 7.0]	-13.7 [-31.2, 8.2]	-13.6 [-31.0, 8.2]	-6.0 [-17.7, 7.4]
Smoker					
smoker (ref)					
non-smoker w/ household smoker	-26.2 [-36.3, -14.4]***	-27.2 [-37.2, -15.6]***	-3.4 [-26.0, 26.2]	-3.9 [-26.3, 25.3]	-27.2 [-37.2, -15.5]***
non-smoker w/o household smoker	-30.4 [-38.0, -21.8]***	-32.4 [-39.7, -24.1]***	-28.1 [-41.3, -11.8]***	-28.2 [-41.4, -12.1]***	-31.7 [-39.1, -23.3]***
Cooking fuel					
clean fuel use (ref:solid fuel)	-15.4 [-22.3, -8.0]***	-15.0 [-21.8, -7.5]***	-1.1 [-14.8, 14.8]	-1.9 [-15.5, 13.8]	-15.4 [-22.3, -8.0]***
Heating fuel					
indoor solid fuel (ref)					
outdoor solid fuel use	-24.6 [-36.9, -9.8]***	-24.2 [-36.5, -9.6]***	-10.5 [-36.7, 26.6]	-11.1 [-37.0, 25.4]	-26.1 [-38.3, -11.5]***

only clean fuel	-2.8 [-12.3, 7.7]	0.1 [-9.6, 10.8]	-1.1 [-17.9, 19.0]*	-4.1 [-20.3, 15.5]*	-1.9 [-11.4, 8.7]
no devices	-1.6 [-16.6, 16.3]	0.1 [-15.2, 18.1]	4.9 [-21.1, 39.4]	2.3 [-23.0, 35.8]	2.0 [-13.7, 20.5]
Season[b]					
non-heating (ref:heating)	-62.8 [-71.8, -50.9]***	-62.3 [-71.4, -50.4]***	-	-	-63.2 [-72.1, -51.4]***
Outdoor concentrations $PM_{2.5}$ per 10 μg/m³*	5.8 [4.7, 6.9]***	5.7 [4.6, 6.8]***	3.4 [1.7, 5.0]***	2.4 [1.3, 3.5]***	5.7 [4.7, 6.9]***
Ambient RH per %	0.8 [0.5, 1.1]***	0.8 [0.5, 1.1]***	1.0 [0.4, 1.6]***	0.7 [0.0, 1.4]***	0.8 [0.5, 1.1]***
Ambient temperature per °C	3.4 [2.2, 4.6]***	3.4 [2.2, 4.6]***	2.2 [-1.0, 5.5]	2.4 [-0.7, 5.7]	3.5 [2.3, 4.7]***
Site					
Guangxi (ref)					
Beijing	37.9 [15.0, 65.3]***	42.2 [18.7, 70.3]***	293.4 [103.1, 662.2]***	254.6 [81.6, 592.7]***	46.2 [22, 75.4]***
Shanxi	69.9 [43.1, 101.6]***	71.8 [44.8, 103.9]***	208.3 [66.3, 471.7]***	187.7 [54.7, 435.0]***	78.7 [50.5, 112.2]***
Marginal R^2	0.24	0.25	0.31	0.31	0.25
Conditional R^2	0.29	0.30	0.46	0.46	0.31

*p-value <0.10; **p-value <0.05; ***p-value<0.001

[a] Regression of log-air pollution exposure can be converted to the percent (%) change in exposure using the equation ($[\exp^{\beta} - 1] \times 100$), where β is the change in log-transformed pollution exposure associated with a one-unit change in the independent variable.

Chapter 4: Objective 2

4.1 Preface

In Objective 1, I focused on personal exposure to air pollution in the Chinese adults living in rural areas: the levels of exposure; the variation within and between participants; and the energy, housing, and sociodemographic predictors of exposure. For Objective 2 I investigate whether exposure to the residential coal-to-clean-energy program is associated with changes in satellite-derived outdoor $PM_{2.5}$ in Beijing using a Bayesian spatiotemporal model to evaluate the association between monthly average satellite-derived air pollution for heating season months (December to February) between December 2014 to December 2019 at the ~1×1km grid cell spatial resolution and participation of these grid cells in the residential coal-to-clean policy. Participation was characterized using a binary variable indicating any villages in the grid cell was participating in the policy. A variable estimating the number of households enrolled in the policy in each grid cell was also created for an interaction term.

This chapter contributes to the overarching theme of household energy and its impacts on air pollution and health in this thesis by contributing to the limited empirical evidence on the impacts of household energy policies on air pollution. This study evaluates the air pollution impacts of a large-scale residential coal-to-clean energy policy across the large geographic regions of Beijing, China. Therefore, it has a benefit informing policy makers on the potential impacts of such a policy.

This manuscript is in progress and has not yet been submitted to a journal.

4.2 Effects of the Coal-to-Clean Energy Policy on Local Satellite-Derived Air Pollution in Beijing, China

Abstract

Beijing has implemented many policies aimed at improving regional air quality over the past decade, including the residential coal-to-clean energy policy which banned residential coal burning and subsidized the cost of replacement gas and electric heaters and electricity in rural and peri-urban areas. We conducted a longitudinal study from December 2014 to December 2019 to assess whether area-level exposure to the policy is associated with changes in local outdoor $PM_{2.5}$ during the heating season. We obtained monthly satellite-derived $PM_{2.5}$ at high spatial resolution (0.01°×0.01° grid cells) for Beijing from December to February (heating season months). For each spatial unit and time point, we developed an area-level measure of exposure to coal-to-clean energy policy, defined as any villages in the area participating in the policy at that time point. We modeled the relationship between $PM_{2.5}$ and exposure to the policy using a hierarchical spatiotemporal model that accounts for the complex spatial and temporal structure of the data. Inference followed the Bayesian paradigm where we used an integrated nested Laplace approximation (INLA) with Stochastic Partial Differential Equation method. Of the 3030 rural and peri-urban grid cells in Beijing with villages, 2032 (67%) had at least one village exposed to the policy by December 2019. Though regional air pollution across Beijing decreased during the study period, we did not find evidence that local exposure to the coal-to clean-energy policy influenced outdoor satellite-derived $PM_{2.5}$, a result that contrasts with other field and modeling studies.

Introduction

The Beijing region has historically been characterized by poor air quality, especially in the winter heating season, due to local emissions of air pollutants, stagnant meteorological conditions, and its regional geography (185). The residential sector is an important source of $PM_{2.5}$ in Beijing and throughout China where hundreds of millions of households burn biomass and coal for cooking and space heating (186, 187). Household coal stoves have higher emission factors than coal burned in the industrial and power sectors due to less efficient combustion

(70). In 2015, household coal stoves contributed nearly half of wintertime outdoor $PM_{2.5}$ in northern China (188) and an estimated ~30% of the outdoor $PM_{2.5}$-attributable premature deaths (189). Regional modeling studies estimated that large-scale household energy transition from coal to electricity or gas could reduce outdoor $PM_{2.5}$ in Beijing by 11-17% (190, 191), a result supported by cross-sectional field studies that measured lower indoor $PM_{2.5}$ in villages that had recently transitioned to gas or electric stoves compared with nearby villages using coal heaters (141, 192).

To mitigate the air quality and health burdens of residential heating, Beijing implemented a residential coal-to-clean energy policy[2] in peri-urban and rural villages as part of its national Air Pollution Prevention and Control Action Plan (185). The policy required villages to stop using coal-fueled heaters and, to ease this transition, provided subsidies for the purchase and installation of electric or gas-powered heaters and the cost of electricity and gas for three years (141, 193). The policy was piloted for several years with large-scale implementation starting in 2016 (140, 194), where villages closer to central (urban) Beijing entered the policy earlier and those in more remote and mountainous regions of Beijing entered into the policy later. Villages did not know if and when they would be enrolled in the policy, as some were required to enter whereas others applied to the policy and were selected by the government (185). The type of fuel (e.g., electricity or gas) was determined by local infrastructure, with the majority of villages shifting to electricity (140, 141).

The effectiveness of large-scale household energy programs in achieving air quality improvements has rarely been empirically investigated, especially at sub-city resolutions. Thus whether large-scale household energy transition improves outdoor air quality has not reached consensus. In Ireland a series of county-level residential coal bans in the 1990s were associated with 40-70% decreases in black smoke concentrations in ban-affected areas (146). In Central Launceston in Australia, a wood-burning stove exchange was associated decrease in average

[2] This policy is referred to by different names including the ‘clean winter heating plan（北方地区冬季清洁取暖规划）and the “clean energy for rural heating” plan (农村采暖用能清洁化)

daily wintertime coarse particular matter (PM_{10}) from 44 μg/m^3 to 27 μg/m^3 (147) and clean energy policies in Christchurch and Timaru, New Zealand were also associated with reductions in wintertime PM_{10} (36% and 11% respectively) (149). Studies of the coal-to-clean energy policy at the municipal- or prefecture-level in northern China observed smaller decreases in $PM_{2.5}$ (2.4 -7 μg/m^3) in regions exposed to the policy compared with neighboring municipalities or regions not exposed to the policy (195-197).

We aimed to evaluate the effect of exposure to the coal-to-clean energy policy on outdoor $PM_{2.5}$ at fine spatial resolution (~1 × 1 km) in Beijing. To our knowledge, no previous studies have evaluated the very local effects of this policy on $PM_{2.5}$ across Beijing, which are less likely to be impacted by other air quality policies, or statistically accounted for spatial correlation in air pollution. Quantifying the local air pollution impacts of this large-scale clean energy program is timely for decision-makers as they consider further expansion of the program across China and to other regions of the world where residential emissions are important contributors to local and regional air pollution.

Methods

Study area

Our study was conducted in Beijing, an area of ~16,400 km^2 that has long served as the political, cultural, and educational center of China. Beijing comprises 16 districts and has a population of ~21 million. Its densely-populated urban core is surrounded by several satellite towns and peri-urban and rural villages in the periphery (198). Beijing winters begin in late October and tend to be cold, dry, and windy, with the lowest outdoor temperatures usually occurring in January (−3.0°C on average) (199). Residential space heating is common and coal-fuelled heaters have historically been used to heat homes (186).

Study design

We conducted a longitudinal study to assess whether local outdoor $PM_{2.5}$ in Beijing was impacted in areas where villages participated in the coal-to-clean energy policy. To capture the time period when air quality is likely most impacted by a winter heating policy, we restricted our study period to the months of December, January, and February which fall fully within the winter heating season that is generally from November 15 to March 15 (200).

Satellite-derived local $PM_{2.5}$

We obtained monthly 0.01° × 0.01°(~1 × 1km) resolution surfaces of $PM_{2.5}$ concentrations from the Atmospheric Composition Analysis Group at the University of Washington in St. Louis (201). Detailed information on the methods used to generate these surfaces can be found elsewhere (56). Briefly, ground-level $PM_{2.5}$ was estimated by combining aerosol optical depth (AOD) retrievals from remote sensing products (Moderate Resolution Imaging Spectroradiometer [MODIS] Dark Target, MODIS and Sea-Viewing Wide Field-of-View Sensor [SeaWiFS] Deep Blue, MODIS Multiangle Implementation of Atmospheric Correction [MAIAC], Multiangle Imaging Spectroradiometer [MISR]) with a GEOS-Chem chemical transport model. The estimates were calibrated with ground-based measurements from China's national air quality monitoring network, which includes 35 reference-quality $PM_{2.5}$ monitors in Beijing, using a geographically weighted regression. Globally, when comparing the hybrid model to measurements from the World Health Organization's Ambient Air Quality database, including the majority of monitors in China, the mean R^2 ranged from 0.81 to 0.86, with the highest correlation in January (56).

We extracted monthly average $PM_{2.5}$ estimates for each 0.01° × 0.01° grid cell in Beijing for the heating season months (December, January, and February) from December 2014 to December 2019, resulting in dataset of 277,776 observations for 17,361 grid cells over 16 winter months (**Figure S1**). The values for 68 missing grid cells were imputed based on the mean of the neighboring eight grid cells.

Geolocating villages in Beijing

We used Baidu Maps (202) to geolocate a list of 7,168 administrative villages and communities in Beijing in 2019 that was obtained from China's National Bureau of Statistics (203) using the village or community, township, and district names. A second list of 2,544 villages that entered the coal-to-clean energy policy between 2015 and 2019 (i.e., exposed villages) which included the district, township, administrative village name, and year of entry was obtained from the College of Urban and Environmental Sciences at Peking University. We removed duplicate villages (n=25) and matched the list of villages exposed to the policy with the geolocated dataset of Beijing villages and communities using their village, township, and district names while also considering similar names or alternative spellings in the same township or a neighboring township using Baidu Maps (202) and Baike (204). Ten villages listed as enrolled in the policy were excluded from the analysis because they either could not be geolocated (n=5) or were no longer independent administrative villages by 2019 (n=5). Nineteen villages listed as enrolled in the policy were not listed in the government database of villages and communities and were added to our administrative dataset after identifying their locations on Baidu Maps (202) and verifying their presence on Baike (204).

Our final dataset of villages contained 2,509 villages exposed to the coal-to-clean energy policy out of 7,187 villages and communities in Beijing. Most villages were listed as having entered the policy in one year, but some entered the policy over two (n = 718), three (n = 141), or four (n = 5) years. For this analysis, we considered villages as exposed to the policy in their first year of entry with the conservative assumption that most households could be participating in the policy at this time. Though villages in Beijing continued to join the policy past 2019, we did not have data on village participation after December 2019.

We transformed the final village dataset into a raster with grid cells to match the same $0.01° \times 0.01°$ spatial resolution as $PM_{2.5}$. For each grid cell and study month, we calculated the total number of villages in each grid cell (median: 0; range: 0-12) and the number of villages exposed to the policy in each grid cell (median: 0, range: 0-8).

Estimating exposure to the coal-to-clean energy policy

Exposure to the policy was characterized for each study month and grid cell for the statistical analysis. We generated a binary variable where grid cells were considered exposed to the policy if they had a village participating in the policy in that month and year, and otherwise as unexposed. Since it was assumed most villages transitioned during the non-heating months (141), we considered villages exposed into the policy starting in December of the year they were enrolled. We chose a dichotomous exposure rather than using proportion of the grid cell treated because most grid cells only had one village and only a small proportion of grid cells (0.7%) had percentage of villages exposed that was not 0 or 100% (**Figure S1**). We did not define exposure by households enrolled in the policy due to the zero inflated distribution, lack of data on spatial variation on village size throughout Beijing, and concerns of residual confounding between the exposure and $PM_{2.5}$ as areas with more households entering into the policy would likely have more emissions.

Covariates

We obtained or derived spatial-temporal variables that could be plausibly associated with the emission, dispersion, or attenuation of local $PM_{2.5}$ and with the likelihood of being exposed by the coal-to-clean energy policy. Covariate selection was guided the by literature on air pollution in northern China (205, 206) and observations of the policy's implementation (140, 141).

Detailed information on covariates is provided in **Table 1**. We included an indicator variable to identify urban grid cells that were likely already connected to the public heating system in 2015 and thus not eligible for the policy. Grid cells were considered urban if 1) located within the boundary of the 5^{th} Ring Road, which is a commonly used landmark to distinguish Beijing's urban core from its less-developed periphery (207, 208); 2) the majority of villages in the grid cell were formally designated as urban by the government, or 3) the population density of the grid cell was over 8258 persons/km^2, which is the 97^{th} percentile for exposed grid cells (209). The number of villages in the grid cell was included in the model to adjust for the total population in the grid cell.

We included elevation because lower elevation areas tend to be more developed, have higher levels of $PM_{2.5}$ and were also more likely to participate in the policy than more remote regions.

Impervious surface indicated a greater presence of anthropogenic activities which can impact levels of air pollution but also indicated a greater presence of infrastructure that facilitated selection into the policy (205). Local meteorological conditions and weather patterns can affect outdoor $PM_{2.5}$ (210, 211) and may also influence energy patterns and preferences and thus village application to the policy. Relative humidity was calculated from temperature and dew point temperature using the August-Roche-Magnus approximation method (212). We calculated monthly averages of the meteorological data to match the temporal resolution of the $PM_{2.5}$ data for statistical analysis. Population density was only used for the sensitivity analysis.

Table 1: Description of covariates included in the spatial-temporal model

Variable *(type)*	**Level of variables**	**Units**	**Temporal resolution in model**	**Spatial resolution in source data**	**Source**
Number of villages *(raster)*	0 to 12	Villages	Annual (from 2019)	-	National Bureau of Statistics of China (203) Baidu Maps (202)
Urban *(raster)*	0 or 1	0 = peri-urban or rural grid cell 1 = urban grid cell classification	-	-	National Bureau of Statistics of China (203) NASA Socioeconomic Data and Applications Center (209)
Global Man-made Impervious Surface (GMIS) *(raster)*	0 to 100	Percent impervious surface	Annual (from 2010)	30m x 30m	NASA Socioeconomic Data and Applications Center (213, 214)
Population Density *(raster)*	0 to 92,900	Population per km^2	Averaged from 2015 and 2020	~1km x 1km	NASA Socioeconomic Data and Applications Center (215)
Elevation above sea-level *(raster)*	8 to 2065	Meters	-	Zoom 11 54m x 54m (at 45°)	Mapzen and Amazon Web Services Terrain Tiles accessed via *elevatr* package (version 0.4.2) (216)

Surface temperature (2m) *(raster)*	-14 to 2	Celsius	Monthly (averaged from hourly data) 30km x 30km ERA5 reanalysis from the European Center for Medium-Ranged Weather Forecasts (217)
Relative humidity *(raster)*	26 to 66	Percentage	
Total precipitation *(raster)*	0 to 0.0003	Meters (of water equivalent per hour)	
U wind *(raster)*	-0.3 to 3	Meters per second	
V wind *(raster)*	-2 to 0.2	Meters per second	

Note: All covariate data were in raster format. The values for each observation were extracted at the midpoint of each 0.01° × 0.01° grid cell.

Proposed spatiotemporal model

We used a model-based approach t**Error! Bookmark not defined.**o investigate whether area-level exposure to the coal-to-clean energy policy is associated with the levels of outdoor $PM_{2.5}$. The observed $PM_{2.5}$ measurements are derived from satellite images and chemical-transport models and considered at the grid cell level. As these observations are highly correlated across space and time, we used a hierarchical spatiotemporal model that assumes:

$$PM_{2.5_{it}} = \beta_0 + \beta_1 exposure_{it} + \sum_{m=2}^{M} \beta_m x_{mit} + \omega_{it}$$

where i is the location unit (i.e., grid cell of the observation), t is the time unit (i.e., heating season month from Dec 2014 to Dec 2019), β_0 is the intercept, β_1 is exposure to the policy for unit *i* and time *t*, $\beta_2, \dots, \beta_m$ are the covariates (e.g., elevation, land use, and meteorological variables) $x_2, \dots, x_m$, and ω_{it} is a latent spatiotemporal effect which is added to capture any remaining spatial structure after accounting for covariates (i.e. not captured by the fixed effects). By accounting for spatial autocorrelation in the latent effect we remove random spatial variations from the general association between exposure to the policy and outdoor $PM_{2.5}$

while also accounting for background temporal trends to remove structure of temporal dependence between time points. This latent component is modelled using a local autoregressive structure, more specifically,

$$\omega_{it} = a\omega_{i(t-1)} + \xi_{it}$$

where a is an autoregressive parameter with $|a| < 1$ which results in a temporally stationary process, and ω_{i1} is assumed to follow a stationary distribution of Normal($0, \sigma^2/(1 - a^2)$), ξ_{it} is a zero-mean Gaussian process that is temporally independent and spatially structured with a Matérn covariance function (218). All the continuous covariates (elevation, land use, and meteorological variables), except for number of villages, were scaled (centred and then standardized) for analysis.

We followed the Bayesian paradigm to estimate the parameters of the model, which means that model specification is complete after assigning a prior distribution to the parameter vector. We assume prior independence among the model parameters. Regardless of the prior specification, the resultant posterior distribution is unknown. Because of our high-dimensional data, we used an Integrated Nested Laplace Approximation (INLA) to obtain estimates of the resultant posterior distributions. In particular, the Gaussian process ξ_{it} was approximated using the stochastic partial differential partial equation (SPDE), as described in detail elsewhere (218). The SPDE approach, together with INLA, is implemented in the R-INLA package (4). Weakly informative priors were used in this study, the defaults of the R-INLA package (4). For all fixed effects, we assigned a zero-mean Gaussian distribution with precision equal to 0.001. We used penalized complexity priors for the Matérn field hyperparameters because this penalized deviation from the base model priors can reduce over-fitting (5, 6). The precision parameters were assigned a gamma prior with both shape and rate set to 0.01.

All areas of Beijing were included in the analysis including those considered not eligible for the policy (e.g., without villages or designated as urban) because the model has a spatial component and removing ineligible grid cells would leave gaps in the surface used to estimate the continuous spatial autocorrelation effect and prevent the model from correctly estimating the coefficients.

As sensitivity analyses, we conducted our analysis 1) only considering grid cells as exposed to the policy when all villages in the grid cell were participating (n =1,894 grid cells by December 2019); 2) at a larger-spatial resolution (n = 2800 grid cells at 0.1° × 0.1°, or ~11km × 11km) using less-resolved $PM_{2.5}$ surfaces from the Atmospheric Composition Analysis Group at the University of Washington in St. Louis (201); and 3) adjusting for population density, which may better account for population and possibly the presence of other air pollution sources than number of villages but is estimated from lower-spatial resolution population data with a high-degree of error and is spatial misaligned with our village dataset.

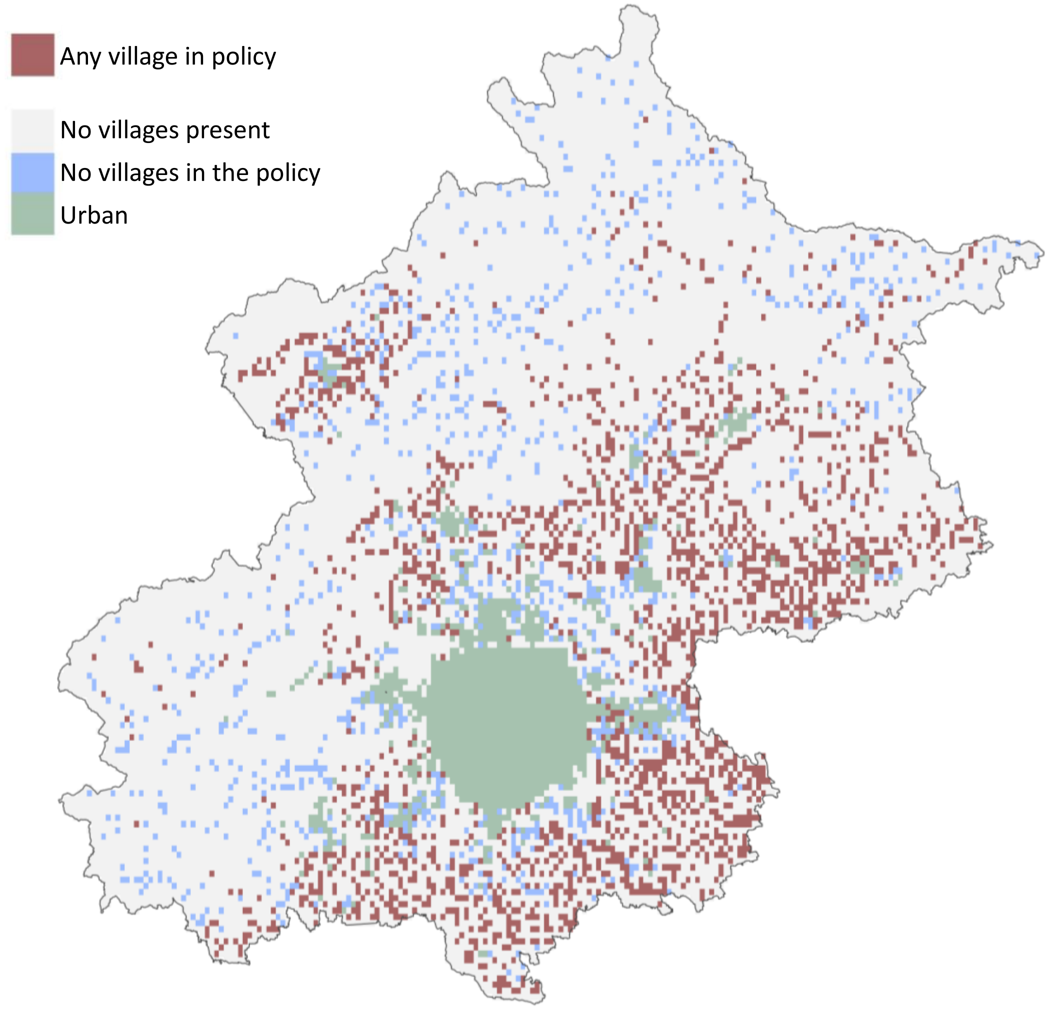
All analyses were done in R (version 4.0.3) (8) using the R-INLA package (4).

Results

The study region was characterized by high concentrations of $PM_{2.5}$ throughout the study period (**Figure S2**). Mean $PM_{2.5}$ across all grid cells and study years was 65 μg/m^3 (median: 64; min/max: 17/114). The urban core had the highest $PM_{2.5}$ with a strong regional gradient in the peri-urban and rural areas characterised by lower $PM_{2.5}$ in northern and northwestern Beijing and higher concentrations in the southern and eastern regions (**Figure S1**). Areas of northwestern Beijing most often met the Chinese national standard for annual $PM_{2.5}$ of 35 μg/m^3 (64). Wintertime $PM_{2.5}$ generally decreased across Beijing over the study period, through the decreases were not spatially or temporally uniform. There were small increases in $PM_{2.5}$ over time in the southwest and, across the province, $PM_{2.5}$ levels in January 2019 were higher than the December or February of the same year but lower than Januarys in earlier years.

Of the 3030 rural and peri-urban grid cells in Beijing with villages, 2032 (67%) had at least one village exposed to the policy by December 2019. Villages in peri-urban and rural areas near the urban core and in the southeast of Beijing were more likely to be exposed to the policy than villages in the more remote, northwestern areas (**Figure 1**).

Figure 4: Map of the study area in Beijing showing grid cells where at least one village was exposed to the policy by December 2019



Note: Grid cells were defined as urban if: 1) located within the boundary of the 5th Ring Road, 2) the majority of villages were formal designated as urban by the Beijing government, or 3) the population density of the grid cell was over 8258 persons/km^2.

Grid cells exposed to the coal-to-clean energy policy had, on average, higher pre-policy levels of $PM_{2.5}$ (61.9 μg/m^3) than unexposed grid cells (57.7μg/m^3) (**Table 2**). Grid cells exposed to the policy tended to be more developed, at lower elevation, and have warmer wintertime outdoor temperature than unexposed grid cells, though meteorological conditions were similar. These differences reflect the implementation patterns of the policy which started in the more developed areas in the plains region that was closer to central Beijing.

Table 2: Pre-policy air quality, land use, and meteorological characteristics (mean [standard deviation] or n [%]), by exposure group. Grid cells with a village participating in the coal-to-clean energy policy by 2019 are classified as 'exposed' and otherwise as 'unexposed'

Characteristics	Exposed (n=2122 grid cells)	Unexposed (n=15239 grid cells)
Satellite-derived outdoor $PM_{2.5}$ (μg/m^3) *mean [sd]*	61.9 [9.4]	57.7 [11.6]
Number of villages *mean [sd]*	1.3 [0.8]	0.3 [0.9]
Classified as 'urban' *n [%]*	90 [4.2]	1235 [8.1]
Impervious surface (%) *mean [sd]*	18.9 [28.7]	12.3 [26.4]
Elevation (m) *mean [sd]*	126 [182]	402 [360]
Outdoor temperature (°C – monthly) *mean [sd]*	-2.6 [1.5]	-3.8 [2.0]
Relative humidity (% – monthly) *mean [sd]*	36.0 [1.2]	36.6 [1.6]
Total precipitation (m of water equivalent per hour – monthly) *mean [sd]*	2.6e-6 [8.2e-7]	2.6e-6 [8.3e-7]
U wind (m per second – monthly) *mean [sd]*	1.1 [0.5]	1.3 [0.6]
V wind (m per second – monthly) *mean [sd]*	-1.0 [0.3]	-1.1 [0.3]

Note: Percentages were calculated as column percentages, with the number of grid cells of that exposure group as the denominator.

In our multivariable analysis, we did not find evidence that exposure to the policy had an effect on satellite-derived outdoor $PM_{2.5}$ (**Table 3**). Exposure to the policy, as defined as a village in the grid cell participating in the policy, was associated with a very small decrease of -0.01 μg/m^3 [95% CrInt: -0.05, 0.03] in $PM_{2.5}$ and credible intervals included the null. The results of our sensitivity analyses were generally consistent with the main analysis (**Table S1**, except for the analysis at a higher spatial resolution which showed a small positive association between exposure to the policy and $PM_{2.5}$, though the credible intervals also included the null (0.097 [95% CrInt: -0.178, 0.372]).

Table 3: Effects of area-level (~1x1 km grid cell) exposure to coal-to-clean energy policy, defined as a village in the grid cell participating in the policy, on local satellite-derived $PM_{2.5}$ (μg/m3) in Beijing and 95% credible intervals.

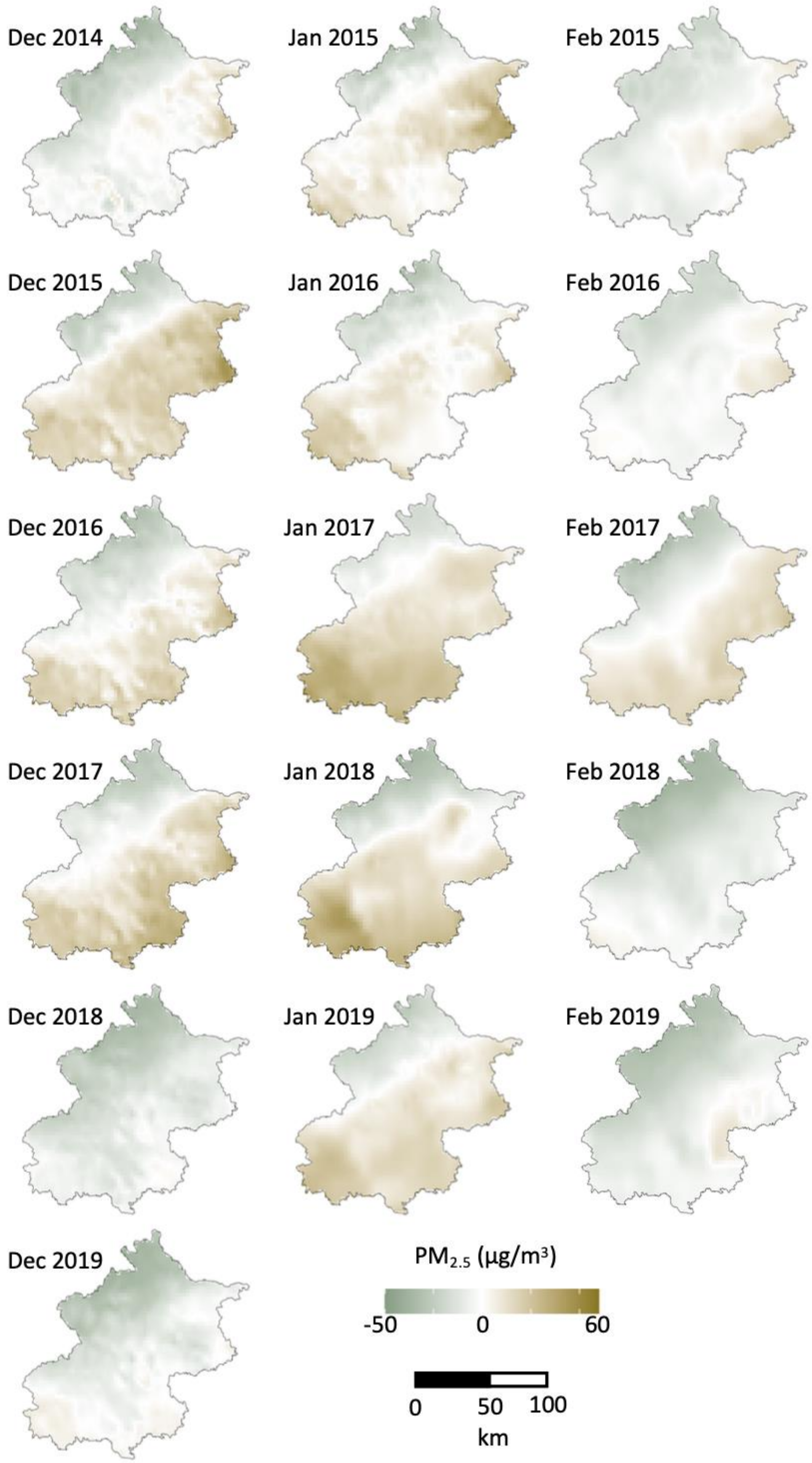
Variable	Coef. [95% credible intervals]
Exposure to the coal-to-clean energy policy	-0.010 [-0.046, 0.026]
Urban grid cell	0.047 [-0.002, 0.096]
Number of villages (per 1 village)	0.005 [-0.006, 0.015]
Relative humidity (per 1 SD increase)	-0.156 [-0.347,0.035]
Outdoor temperature (per 1 SD increase)	-0.340 [-0.436,-0.243]
Elevation (per 1 SD increase)	-0.022 [-0.047,0.003]
Impervious surface (per 1 SD increase)	0.023 [0.013,0.034]
Total precipitation (per 1 SD increase)	-0.130 [-0.280,0.020]
V wind component (per 1 SD increase)	-0.015 [-0.090,0.059]
U wind component (per 1 SD increase)	-0.279 [-0.347,-0.211]

SD, standard deviation

Continuous covariates (relative humidity, outdoor temperature, elevation, imperious surface, total precipitation, and wind components) were scaled (centred and then standardized) for analysis. Their coefficients represent the associated change in $PM_{2.5}$ for a one standard deviation increase from the mean.

The latent effects (unobserved heterogeneity) accounting for the spatiotemporal effects were similar across models in the main and sensitivity analyses. Mirroring what we observed for $PM_{2.5}$, the latent effects also decreased over the study period (**Figure 2**) and were, on average, largest in January and smallest in February. By the end of the study period, the latent effects were near zero or negative across all of Beijing. Generally, we observed a strong northwest to southeast gradient from low to high.

Figure 2: Monthly posterior mean of the latent spatiotemporal effects with exposure defined as having a village in the grid cell participating in the policy during the study period in Beijing



Discussion

In this Beijing-wide study of the coal-to-clean energy policy, we did not find evidence that exposure to the policy reduced satellite-derived outdoor $PM_{2.5}$ at the small area-level, though we did observe a considerable regional decrease in $PM_{2.5}$ over the study period. The estimated decrease in $PM_{2.5}$ associated with the coal-to-clean energy policy was a very small, 0.01 $\mu g/m^3$, and the credible intervals included the null.

Important strengths of our study are its highly spatially resolved data and our ability to account for both spatial and temporal correlation of area-level $PM_{2.5}$ by fitting a hierarchical spatiotemporal model. Previous empirical studies of the policy are mostly limited to much larger-scale estimation at regional or municipal-scales, which are highly subject to influence by other air quality policies or development impacts. By comparison, our study was conducted at the small-area level to capture local levels of $PM_{2.5}$ and participation in the policy. This may reduce the potential influence of other air quality policies (e.g. regional reductions in industrial coal burning). Further, our spatiotemporal model does not assume spatial independence and is better able to quantify the uncertainty parameters of the model by correctly accounting for the complex spatial structure of the data.

Our findings contrast with the relatively large decreases in outdoor air pollution associated with residential fuel use inventions in the previous studies, though most were conducted at a much larger spatial resolution than our analysis. A residential coal ban in Ireland was associated with a 40 to 70% decrease in black smoke in exposed counties (146). The wood-burning stove exchange program in Launceston, Australia was associated average daily wintertime ambient PM_{10} decrease from 44 $\mu g/m^3$ to 27 $\mu g/m^3$ within the city (147). An air quality-dependent wood burning ban in the San Joaquin Valley Air Basin was associated with a 12% decrease in regional $PM_{2.5}$ (148), and a ban on solid fuel burning and open fires paired with a residential clean heater replacement program in Christchurch, New Zealand was associated with a 41% reduction in ambient PM_{10} within the city (149). These studies suggest that clean energy policy can provide an air quality benefit based on measurements from a small number (n=1-6) of local monitoring sites in each city or region conducted before and after the policy, but most lacked a control (comparison) group and none accounted for latent spatiotemporal effects. Thus, the estimates are subject to influence by other unmeasured temporal changes that could affect air quality (e.g., other air quality policies, urban development, or land-use changes).

Our results also contrast with a recent district-level panel study in Beijing by Lui et al. (2020) that estimated a 12% annual decrease in $PM_{2.5}$ throughout Beijing between 2014 and 2018 (219) based on measurements of $PM_{2.5}$ from the government monitoring network. These measurements of $PM_{2.5}$ are more accurate than our satellite-derived $PM_{2.5}$ estimates but limited in their spatial coverage and, along their statistical methods, less able to account for spatial autocorrection than our methods. There was an overall regional decrease in outdoor $PM_{2.5}$ throughout the study period but this reduction was not uniform throughout Beijing. It is possible by accounting for joint spatial and temporal autocorrection, our method adjusted for regional trends, potentially the results of other clean air policies in Beijing or in up wind regions, and correctly removed this noise from the general association between policy exposure and outdoor $PM_{2.5}$.

The lack of impact on outdoor $PM_{2.5}$ in our study may be due to the challenges of identifying the outdoor air quality benefit of an indoor intervention. It is also possible that any small local air quality benefit was masked by relatively high levels of outdoor $PM_{2.5}$ and the complex mixture of regional pollution and local emission sources.

Spillover effects could have further obscured our ability to measure an effect of the policy on air quality. Areas with villages participating in the program could be impacted by coal burning from upwind in villages that have not transitioned, and areas without villages participating in the policy could benefit from lower pollution from nearby areas exposed the policy. This should result in regional decreases in air pollution, as observed in a previous study (219), but the local decreases would be more obscured. We tried to account for some spillover effects by implementing a statistical model that accounts for spatial autocorrelation, though this does not completely remove the effect.

Incomplete adherence to new stoves and continued use of solid fuel stoves in exposed villages could also reduce the outdoor air quality impacts of the policy. Two recent field studies observed continued use of coal in some villages participating in the policy due to a range of factors including the relatively high costs of gas and electricity, reduced energy delivered, and familiarity of coal stoves (140, 220). Another field study of the policy found that, while clean energy use was higher in villages participating in the policy compared with nearby villages not yet participating, lower-income villages continued using their coal stoves (141). In December 2017, the government allowed for temporary coal burning in households enrolled in the policy due to cold weather and incomplete implementation of new heating technologies in some villages participating in the policy, which could also affect the policy's air quality benefit (58, 221).

Our study has several important limitations that could also impact our findings and could be considered in future analyses. First, we relied on satellite-derived $PM_{2.5}$ because high-resolution measurements were not available for all of Beijing. While an advantage of using these highly-resolved satellite-derived data is that they provided continuous surface of $PM_{2.5}$ for the large geographic region of Beijing, the data are spatially-smoothed through modeling and thus less able to capture local variability including the contribution of local sources like household solid fuel burning (201, 222). This may inhibit our ability to observe small local changes in $PM_{2.5}$. Second our area-level exposure variable assumes that village size is consistent which almost certainly introduce measurement error. We did not have data on village area and thus assigned an entire village to a grid cell based on its central coordinate. It is possible that village geographic boundaries crossed multiple grid cells. This error would most likely result be non-differential and lead to an underestimation of the air quality impacts of the policy. Finally, we did not assess the potential impact of spatial confounding, which occurs when the latent spatiotemporal effects are correlated with covariates. If present, it can affect the estimation of the fixed effects (223).

Conclusion

In this study of satellite-derived outdoor $PM_{2.5}$ in Beijing, we observed a notable regional reduction in $PM_{2.5}$ between 2015 and 2019 but did not find evidence that exposure to the coal-to-clean energy policy was associated with changes in outdoor $PM_{2.5}$ at the small area-level.

4.3 Supplementary Information

Figure S1: Histogram of proportion of villages in a grid cell exposed to the coal-to-clean energy policy in December 2019. Analysis limited to grid cells with at least one village

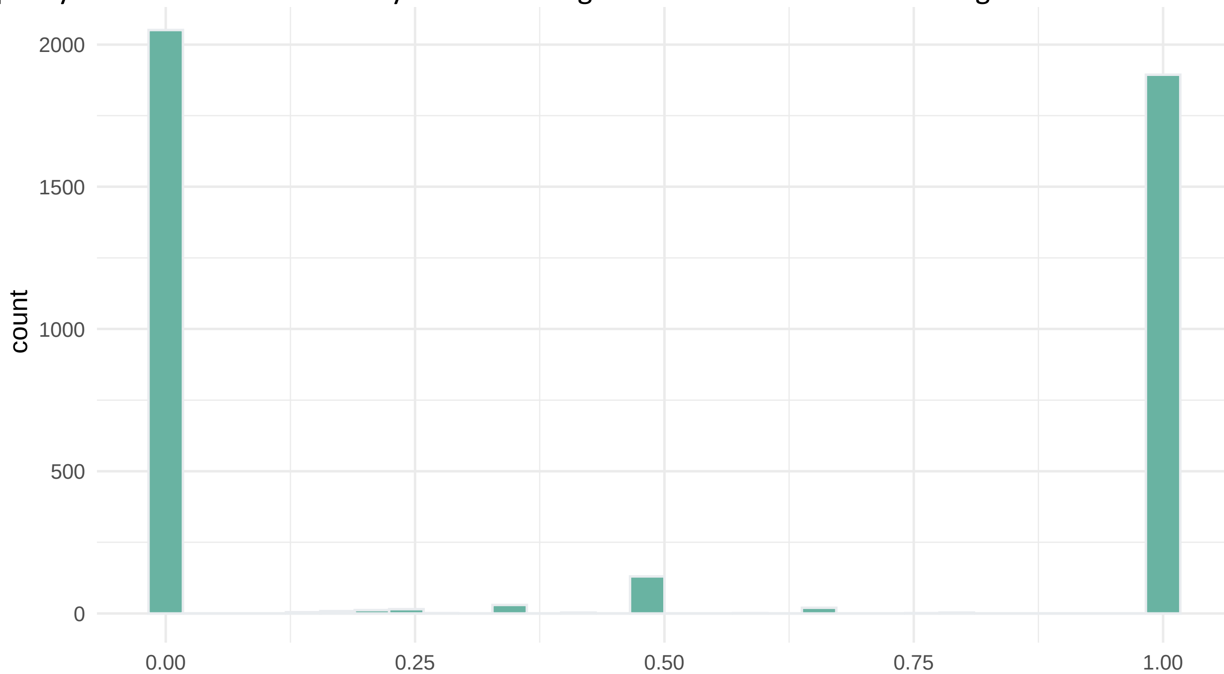


Figure S2: Plots of monthly satellite-derived outdoor $PM_{2.5}$ in Beijing during the study period. Data are from the Atmospheric Composition Analysis Group at the University of Washington in St. Louis. White color indicates that $PM_{2.5}$ levels meet China's national standard for maximum annual $PM_{2.5}$ (35 μg/m^3); blue shading indicates areas where monthly average $PM_{2.5}$ is below the annual standard and red indicates grid cells where monthly average $PM_{2.5}$ is higher than the standard

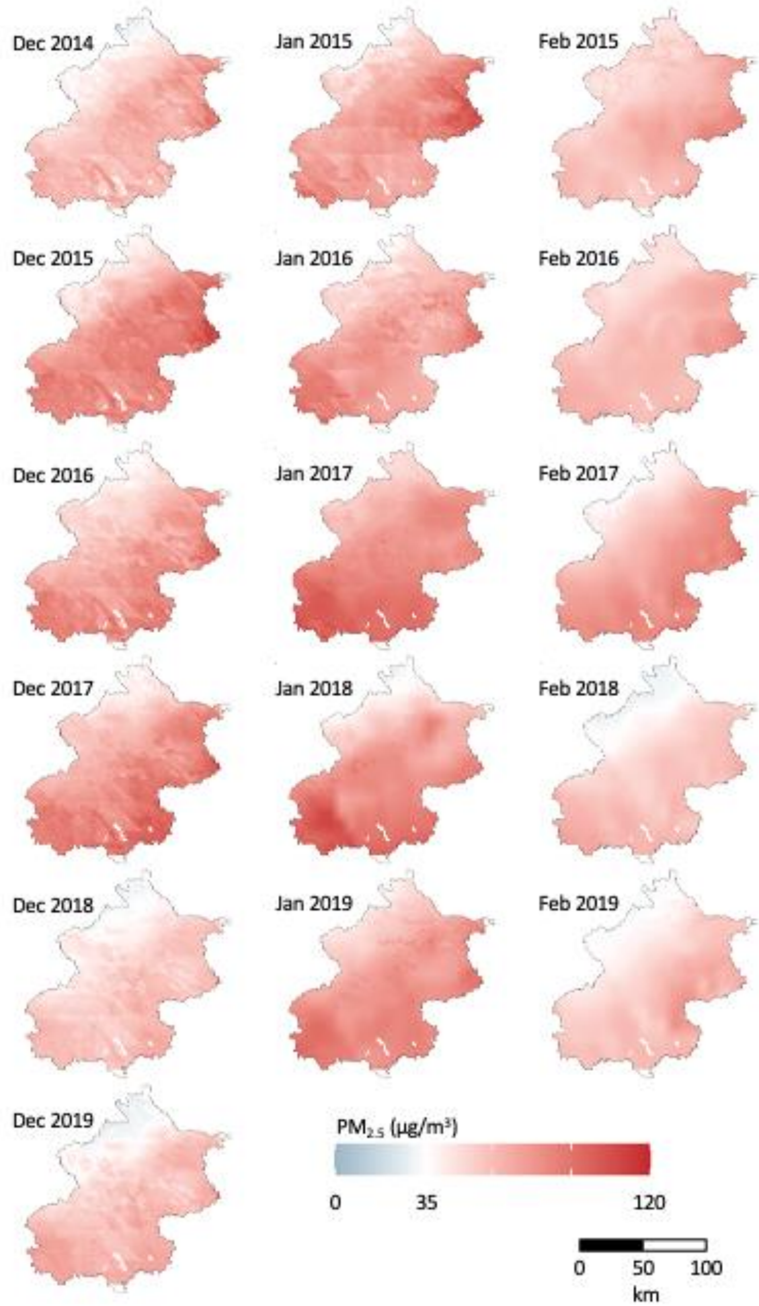


Table S1: Sensitivity analyses of the effects of area-level exposure to the coal-to-clean energy policy on local satellite-derived $PM_{2.5}$ [with 95% credible intervals]

Variable	***Main Analysis***	**(i) 100% of villages in the grid cell participating in the policy**	**(ii) A village in the 0.1°×0.1° (~11×11km) grid cell participating in the policy**	**(iii) A village in the grid cell participating in the policy adjusting for population density**
Exposure to the coal-to-clean energy policy	-0.010 [-0.046, 0.026]	-0.013 [-0.05,0.025]	0.097 [-0.178,0.372]	-0.004 [-0.039,0.030]
Urban grid cell	0.047 [-0.002, 0.096]	0.047 [-0.002,0.096]	-0.352 [-0.692,-0.011]	0.054 [0.008,0.099]
Number of villages (per 1 village)	0.005 [-0.006, 0.015]	0.004 [-0.006,0.015]	0.001 [-0.002,0.004]	0.009 [-0.005,0.022]
Relative humidity (per 1 SD increase)	-0.156 [-0.347,0.035]	-0.153 [-0.344,0.038]	-0.565 [-1.591,0.460]	-0.153 [-0.344,0.038]
Outdoor temperature (per 1 SD increase)	-0.340 [-0.436,-0.243]	-0.339 [-0.435,-0.242]	-0.846 [-1.456,-0.235]	-0.338 [-0.434,-0.241]
Elevation (per 1 SD increase)	-0.022 [-0.047,0.003]	-0.022 [-0.047,0.003]	-0.440 [-0.63,-0.251]	-0.022 [-0.047,0.003]
Impervious surface (per 1 SD increase)	0.023 [0.013,0.034]	0.0230 [0.013,0.034]	-0.150 [-0.254,-0.046]	0.023 [0.013,0.034]
Total precipitation (per 1 SD increase)	-0.130 [-0.280,0.020]	-0.130 [-0.2800,0.02]	0.121 [-0.626,0.869]	-0.129 [-0.279,0.021]
V wind component (per 1 SD increase)	-0.015 [-0.090,0.059]	-0.015 [-0.090,0.059]	0.124 [-0.311,0.559]	-0.015 [-0.089,0.059]
U wind component (per 1 SD increase)	-0.279 [-0.347,-0.211]	-0.280 [-0.348,-0.212]	-0.774 [-1.176,-0.372]	-0.278 [-0.346,-0.210]

SD, standard deviation

Note: Continuous covariates (relative humidity, outdoor temperature, elevation, imperious surface, total precipitation, and wind components) were scaled (centred and then standardized) for the analysis. Their coefficients represent the associated change in $PM_{2.5}$ for a one standard deviation increase from the mean.

Chapter 5: Objective 3

5.1 Preface

In Objective 3, I continued to evaluate the impacts of the Beijing residential coal-to-clean-energy policy by evaluating the impacts of the policy on health. I assessed the effect of treatment by the coal-to-clean-energy policy on incidence of acute myocardial infarction (AMI) in Beijing townships. I leveraged township-level data from Beijing on AMI and participation in the coal-to-clean energy policy from 2013 to 2019, and conducted a multiple time point difference-in-difference analysis to assess whether treatment by the policy affected township incidence of AMI for all adults and separately for different sex and age groups. Township AMI incidence rates for all adults and for separate sex- and age-groups were estimated over one- and two-year periods by a co-first author in China using routinely and systematically collected hospital admissions and mortality data. I defined township-level participation in the coal-to-clean energy policy (treatment) as more than 50% of the villages in the township enrolled in the policy. These analyses included three time points: pre-treatment period (2013-2014), a first post-treatment period (2016-2017), and a second post-treatment period (2018-2019).

This chapter adds to the overarching theme of the thesis by adding to the limited body of evidence on the health impacts of clean energy policies. This study provides stronger casual evidence than a traditional observational study due to its pre-post policy design and inclusion of both treated and untreated townships, and can inform decision makers about the potential cardiovascular benefits of clean energy intervention.

This manuscript is in progress and has not yet been submitted to a journal.

I did not have access to the individual-level data used in this study. The AMI data were accessed and analyzed at Beijing Centers for Disease Control by the other co-first author who is based on China. The study investigators at AnZhen Hospital also obtained approvals from their ethnical review committee and from the Ministry of Science and Technology in China to collaborate with McGill University on this study. I developed the R scripts for descriptive summary statistics, the statistical analysis, and data visualisation in collaboration with the co-first author who conducted the data analysis in China.

5.2 Effect of China's Coal-to-Clean Energy Policy on Acute Myocardial Infarction in Beijing: A Difference-in-Difference Analysis

Abstract

Background: In 2015 the Chinese government launched an ambitious coal-to-clean energy policy that banned residential coal burning and provided subsidies for clean heating technologies and electricity in northern China. The health impacts of this policy have not been empirically assessed.

Objectives: This study aimed to estimate the effects of treatment by the coal-to-clean energy policy on incidence of acute myocardial infarction (AMI) in Beijing townships using data from 2013 to 2019.

Methods: We used a quasi-experimental multiple time-point difference-in-difference approach to estimate the effect of the coal-to-clean energy policy on AMI rates in Beijing townships (n=151). Township-level incidence of AMI was calculated for rural and peri-urban townships from 2013 to 2019 for all adult and separated sex-age groups. Townships were considered as treated in the policy in years when more than 50% of their villages were participating in the policy.

Results and Discussion: We observed an average reduction of -5.5% (95% CI: -11.8%, 1.3%) in AMI incidence per 100,000 population in the post-treatment period compared with the pre-treatment period in the townships treated by the policy relative to untreated townships. The largest effects of treatment were observed among women (-12.1%, 95% CI: -21.2%, -2.0%) and older adults (-12.6%, 95% CI: -20.8%, -3.8%). While estimates for older men show an impact -9.6% (95% CI: -17.5%, -1.2%) these effects disappeared when looking at all men where the estimates included the null and were close to zero. As household energy programs and policies are being scaled up globally, our results provide among the first empirical evidence of cardiovascular benefits attributable to a large-scale clean energy policy. Our results may help to motivate continued investment in such clean energy.

Introduction

Cardiovascular disease is the leading cause of death in China, accounting for approximately 40% of deaths in 2019 (224). Acute myocardial infarction (AMI) is a common and serious form of cardiovascular disease that is often fatal (88, 225). Mortality from AMI has increased sharply over the last decade in China as its population ages (224), making prevention of AMI a policy priority (226).

Recent studies demonstrate convincing associations between incident AMI and environmental exposures like air pollution (151), and that mitigating air pollution may have cardiovascular benefits. In Beijing, air quality control measures during the 2008 Olympics were associated with decreased cardiovascular mortality (227), and smoking bans in public places lowered hospital admissions for AMI by an average of 5% (228).

In 2015 the Chinese government launched a coal-to-clean energy policy[3] to reduce air pollution from household coal burning, which was the primary heating source for many households especially in Northern China (229). Residential coal burning emits high levels of air pollution into homes and contributed to an estimated 30% of wintertime ambient $PM_{2.5}$ in Beijing prior to 2016 (230). The coal-to-clean energy policy aimed to progressively transition up to 70% of coal-burning households in northern China to electric or gas-powered heating by 2021 by banning residential coal burning and subsidizing the costs of electric or natural gas-powered heaters and energy (electricity or gas) (141). Villages were either assigned into the policy or applied to a selection process, and the new heaters were typically installed between March and November (194). By 2020, an estimated 25 million households in the Beijing-Tianjin-Hebei region were participating in the policy (231).

Whether the coal-to-clean energy policy has yielded health benefits has not been empirically investigated. We studied the effects of the policy on incidence of AMI in Beijing townships using

[3] This policy is referred to by several names including the “clean winter heating plan for northern China”（北方地区冬季清洁取暖规划）and the “clean energy for rural heating plan” (农村采暖用能清洁化)

data from 2013 to 2019. The results of this study can inform the potential health benefits of ongoing and planned clean household energy policies in China and globally.

Methods

Study area

Beijing (pop. 21.9 million in 2020) is China's political, cultural, and technical innovation capital. It covers a large geographic area (16,410 km^2) which is administratively divided into six urban districts at its core and ten outlying peri-urban and rural districts. Districts are further divided into townships that contain communities and villages. Beijing winters are cold and dry, with the lowest temperatures occurring in January (average: -3.0°C) (199), thus requiring space heating. Most urban areas of Beijing are connected to the central heating grid that supply heat from central locations whereas rural areas rely on individual space heating units that, prior to 2015, were mostly fuelled by coal (232).

Study design and sample

We conducted a quasi-experimental study to measure the effect of the coal-to-clean energy policy on incidence of AMI in Beijing townships, which is the most resolved spatial resolution for AMI data available. Of the 307 townships in Beijing in 2013, we excluded 156 townships comprised of mostly urban or developed suburban communities with access to centralized heating that were ineligible for the policy. Details on eligibility criteria are described in the SI. Our final sample of 151 peri-urban and rural townships included 29%, or 5.7 million, of the Beijing population, based on the 2010 census.

The study protocol was approved by the ethics review committee at Beijing AnZhen Hospital, Capital Medical University.

Incidence of acute myocardial infarction

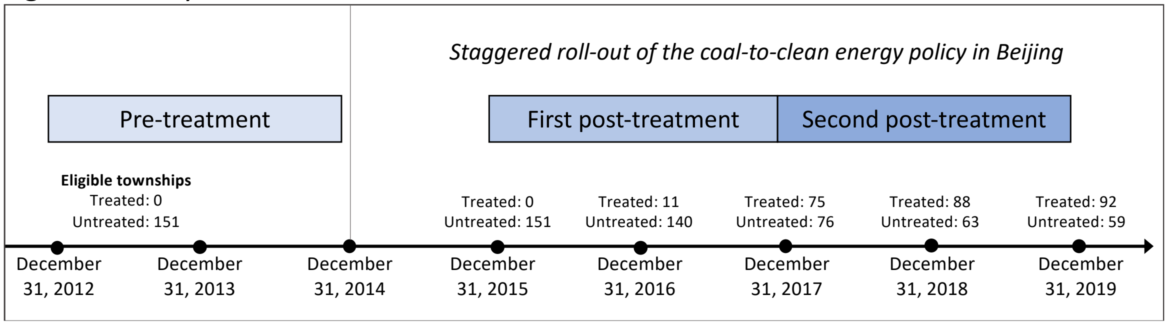
Our outcome was incidence of AMI (calculated as the number of AMI events per 100,000 population) among adult permanent residents in Beijing. The AMI data were extracted for 2007 to 2019 from the Beijing Cardiovascular Disease Surveillance System, which records all secondary- and tertiary- level hospital admissions and deaths for AMI along with patient age, sex, date of onset, and township of residence. Diagnosis was based on principal discharge diagnoses or underlying cause of death with codes I21–I22 (acute myocardial infarction and subsequent myocardial infarction) in the International Classification of Diseases, Tenth Revision (ICD-10). Population data were obtained from district statistical yearbooks. Age-sex standardized rates were calculated using the 2010 Beijing population as reference.

We fitted Bayesian spatial models for township AMI incidence for all adults and separate sex-age groups (35–64y, 65y+, 65-79y, 80y+, stratified based on AMI risk), using methods described elsewhere (233). We pooled AMI events over two-year periods before (2013-2014) and after (2016-2017 and 2018-2019) the policy to create more stable estimates for smaller townships and age-by-sex groups. We excluded 2015 because it was a pilot year for the policy where only a small number (n=18) of geographically dispersed villages were treated. For use in sensitivity analyses, we also estimated 1) single-year township AMI incidence for adults ages 65y+, which are less stable due to a smaller number of events but may better temporally align with timing of treatment, and 2) sex-age specific incidence for two-year time periods starting in November, which is the start of the heating season (234).

Treatment by the coal-to-clean energy policy

We exploited geographic variation in treatment by the coal-to-clean energy policy over time to estimate the effect of treatment on AMI. Detailed information is provided in the SI. Briefly, we obtained a list of villages (n=2509) treated by the policy between 2015 and 2019 along with year of treatment from the College of Urban and Environmental Sciences at Peking University, which we combined with a geolocated database of communities and villages in Beijing from the China National Bureau of Statistics in 2019 (203). We calculated the proportion of treated villages in each township and study period and created a binary treatment variable that considered eligible townships as 'treated' when more than 50% of their villages were participating in the policy, and otherwise as 'untreated' (**Figure 1)**.

Figure 1: Study timeline



Note: Boxes illustrate the pre- and post-treatment periods for which we estimated township incidence of AMI (events per 100,000 population) and treatment by the coal-to-clean energy policy.

Covariates

We assembled a database of covariates that are established risk factors for AMI (224, 235-237). Pre-treatment socioeconomic variables from the 2010 national census included the proportion of population in the township 1) working in agriculture, 2) having completed secondary school education or higher, and 3) unemployed at the time of the census (236). We also obtained time-varying data for cardiovascular risk factors including township rates of current tobacco smoking, obesity (BMI ≥28kg/m^2), hypercholesterolemia (total cholesterol ≥6.22 mmol/L), wintertime average outdoor temperature, and access to health care in each township, defined as the estimated number of secondary and tertiary hospital beds per 1000 population. Details on the data sources and measurement of each covariate are provided in the SI.

Statistical analysis

We summarized and graphically presented the means, medians, and interquartile ranges (IQR) of AMI incidence and covariates for treatment groups over time. We used difference-in-difference (DiD) estimation with multiple time periods and variations in treatment timing (238) to estimate the effect of treatment by the policy on AMI incidence. This approach compares multiple treatment groups over multiple time periods to estimate 1) average treatment effects across different lengths of treatment and 2) global effects that combines the weighted averages of the group-time effects (238).

We conducted linear univariate and multivariable regression models for all adults and separate sex-age groups. We used doubly robust estimations that combine outcome regression with inverse probability weighting by propensity scores to balance covariates between treated and untreated townships and thus reduce the likelihood of confounding (239). Township incidence of AMI was log-transformed to improve the normality of the model residuals.

We presented the global effect of treatment on AMI incidence as well as the dynamic treatment effects, which represents the effect of treatment on AMI at 0-2 years and 3-4 years post-treatment. Point estimates for the average treatment effect on the treated (ATT) were calculated using the finalized AMI rates from the fitted Bayesian spatial models (233). To incorporate the uncertainty from use of modelled AMI incidence as our outcome variable, to calculate the 95% confidence intervals (CI) we conducted the statistical models 6000 times using the 6000 random draws generated from the posterior distributions of the Bayesian model for AMI estimation. We reported the medians of the distributions of the upper and lower 95% CIs values calculated from these 6000 model runs.

Sensitivity analyses and robustness checks

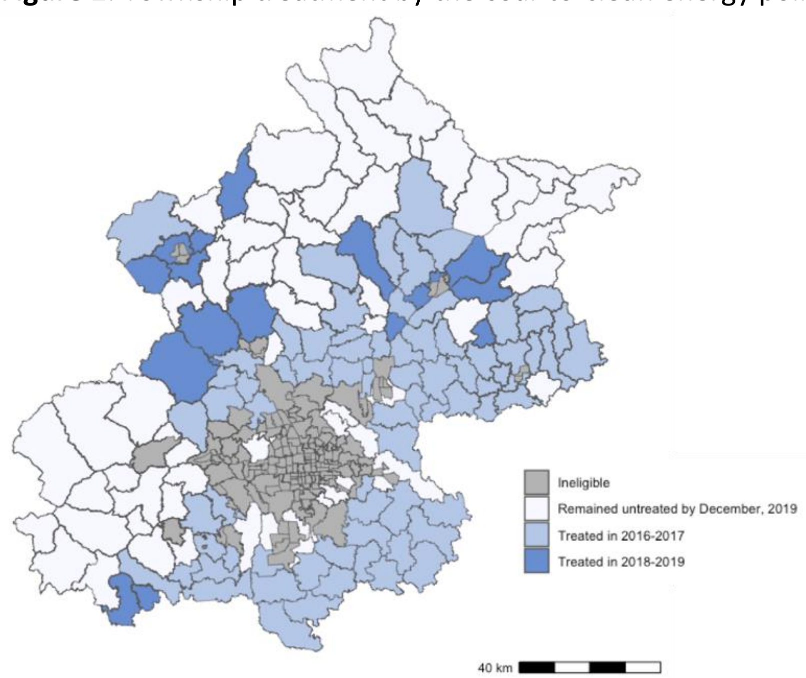
We conducted several alternate specifications of the models to evaluate the robustness of our results, with details provided in the SI. First, we tested the impact of estimating the outcome in three different ways: age-standardization with smaller age groups (35-49y, 50-64y, 65-79y, 80y+) and using different time periods including (i) two-year incidence of AMI starting in November, which coincides with the start of the heating season, and (ii) single-year incidence of AMI for adults 65y+, to potentially better temporally align with treatment. Second, we assessed the influence of outliers by excluding two townships with especially high incidence of AMI that were visually identified using boxplots. Third, we evaluated the impacts of township inclusion criteria by additionally excluding six untreated townships that were eligible for the study based on our criteria but geographically surrounded by ineligible townships. The proportion of villages and communities enrolled in the policy in these six townships ranged from 0 to 50% and their central location, indicated that a large proportion of villages in these townships likely had access to central heating. Fourthly, we included hypercholesterolemia as a covariate. Hypercholesterolemia could be a potential confounder or at least a predictor of AMI events but it could also be along the casual path as there is some evidence of a casual association between $PM_{2.5}$ and hypercholesterolemia (240). Finally, we used a more distinct treatment specification that defined 'treated' as >70% of villages treated and defined 'untreated' as <30% of villages treated, excluding 60 townships with 30-70% of villages treated from the analysis.

All analyses were conducted in R, version 4.2.2, and the *'did'* package (R Foundation for Statistical Computing, Vienna, Austria).

Results

Among eligible townships, the median proportion of villages treated was 65% (IQR: 30-89%) by December 2019 (**Figure S1**). Using our township treatment definition of more than 50% of villages treated, 75 and 92 townships were treated by the end of 2017 and 2019, respectively (**Figure 2**). Townships near the urban core and in the southeast were more likely to be treated than townships in more remote northern and western areas of Beijing.

Figure 2: Township treatment by the coal-to-clean energy policy in Beijing.



Note: Eligible townships were considered treated if more than 50% of villages and communities were participating in the policy. Townships comprised of mostly urban communities connected to central heating were considered ineligible for this study.

Mean and median township AMI incidence in all adults and sex-age groups followed similar temporal trends for different treatment groups in the eight years prior to the start of the policy (**Figure S2)**. In the 2013-2014 pre-treatment period, median incidence of AMI was highest in townships treated in 2016-2017, followed by untreated townships and those treated in 2018-2019 (**Table 1**). The distributions of pre-treatment covariates were similar across treatment groups, though untreated townships tended to have lower wintertime ambient temperature, less access to health care, and lower educational attainment. Township time-varying covariates followed similar trends over time, except for the proportion population with obesity and that smoked where differences between treatment groups converged (**Figure S3-S4**).

Table 1: Township characteristics (median [interquartile range, IQR]) in the pre-treatment period (2013-2014), by treatment group

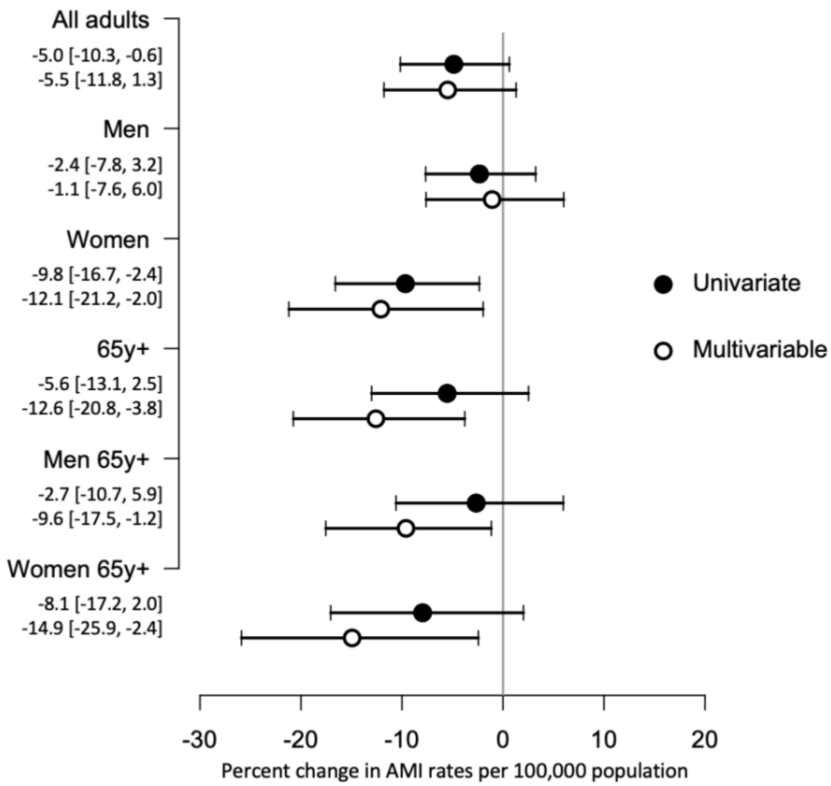
Characteristic	**Untreated (n=59)**	**Treated in 2016-2017 (n=75)**	**Treated in 2018-2019 (n=17)**
Incidence of acute myocardial infarction (events per 100,000 pop)			
All adults	266 [225, 350]	325 [277, 383]	248 [224, 286]
Men	327 [280, 438.6]	406 [356, 487]	309 [291, 380]
Women	192 [161, 247]	226 [198, 283]	177 [158, 223]
Adults 65y+	854 [694, 1064]	1034 [878, 1267]	798 [728, 1015]
Men	890 [773, 1053]	1147 [927, 1382]	907 [673, 1026]
Women	836 [641, 1086]	939 [829, 1262]	794 [652, 1006]
Population working in agriculture (%)	81 [70, 88]	78 [73, 83]	79 [65, 82]
Population unemployed (%)	4 [4, 6]	4 [4, 4]	4 [4, 4]
Population with secondary school education or higher (%)	24 [19, 29]	27 [24, 32]	28 [23, 47]
Population current smokers (%)	25 [22, 32]	24 [21, 28]	31 [20, 32]
Population with obesity (%)	23 [21, 25]	21 [18, 25]	23 [21, 24]
Access to health care (number of hospital beds per 1000 population)	1.4 [0.3, 3.0]	2.4 [1.7, 3.1]	1.9 [1.2, 3.5]
Outdoor temperature (heating season average (°C)	-3.9 [-5.2, -2.8]	-2.7 [-3.3, -2.3]	-3.6 [-5.5, -3.3]
Population with hypercholesterolemia (%)	8 [5, 8]	7 [6, 8]	8 [4, 8]

Note: A township was considered treated if more than 50% of its villages and communities were participating in the coal-to-clean energy policy. Means and standard deviations of township AMI incidence and covariates are provided in **Table S1**. Obesity was defined as having a BMI ≥28kg/m^2. Access to health care is defined to the number of secondary and tertiary hospital beds per 1000 population. Heating season refers to the months of December, January, and February. Hypercholesterolemia was defined as total cholesterol ≥6.22 mmol/L.

The distributions of the confidence intervals from all 6000 iterations of the statistical models generally followed a normal distribution (**Figures S5-S6**), indicating that our presentation of the median confidence intervals represent the central tendencies of the range of possible ATT values.

In the multivariable models with all adults, we observed an overall -5.5% reduction (95% CI: -11.8%, 1.3%) in the township incidence of AMI in the post-treatment period compared with the pre-treatment period in the townships treated by the policy relative to untreated townships (**Figure 3**). Treatment by the policy had larger effects on AMI incidence among women (-12.1%, 95% CI: -21.2%, -2.0%) and older adults (-12.6%, 95% CI: -20.8%, -3.8%). We did not find an effect of the policy on AMI in models that included men of all ages, though we did observe an effect in the sub-group analysis with men ages 65y and older (-9.6% 95% CI: -17.5%, -1.2%).

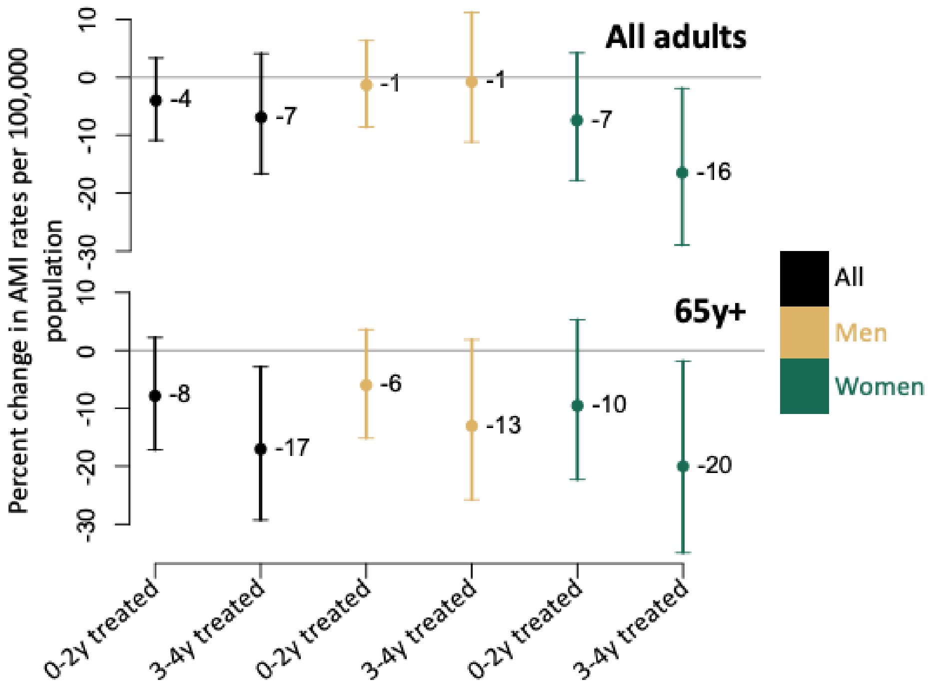
Figure 3: Overall global weighted average treatment effect on the treated (ATT) per 100,000 population and 95% CI of the coal-to-clean energy policy on incidence of acute myocardial infarction in Beijing townships, by sex and age group. Results from univariate and multivariable multiple time-point models difference-in-difference models



Note: Dichotomous treatment representing townships with more than 50% of villages treated by the policy. Effect estimates are presented as the percent change in the incidence of AMI, calculated as (exp(coef)-1)*100 to account for the log-transformed outcome.

The dynamic treatment effect specification showed a general trend of in greater reduction in township AMI incidence for townships treated longer (3-4y) versus shorter (0-2y). (**Figure 4**).

Figure 4: Dynamic aggregate group-time average treatment effect on the treated (ATT) per 100,000 population and 95% CI of the coal-to-clean energy policy on incidence of AMI in Beijing townships by sex and age-group. Results from multivariable models. Coefficients represent the ATT after 0-2 years of treatment and after 3-4 years of treatment



Note: Townships considered treated when more than 50% of villages in the township were treated by the policy and otherwise as untreated. Relative ATT estimates are presented as percent change in AMI, calculated as (exp(coef)-1)*100 to account for log-transformed AMI rates

The results from our sensitivity analyses were consistent with findings from the main analysis, which indicated a benefit of the policy on township AMI incidence (**Tables S2**), with several notable differences. The use of single-year AMI rates as the outcome in models limited to older adults produced smaller point estimates than in main analysis. Using more conservative treatment and untreated thresholds resulted in larger estimated effects of the policy on AMI in older adults and in men. Additionally adjusting for hypercholesterolemia also resulted in slightly larger estimated reductions in AMI than what we observed in the main analysis.

Discussion

In this quasi-experimental study, we found a 5.5% overall reduction in the incidence of AMI per 100,000 population in townships where more than 50% of villages were participating in the policy, indicating a cardiovascular benefit of the coal-to-clean energy policy. We observed larger reductions in AMI incidence in population subgroups including women and older age adults and in townships considered treated for longer. The estimated AMI benefits of treatment by the policy persisted in extensive sensitivity analyses.

Strengths of our study are the population-based assessment of a large-scale energy policy using a quasi-experimental design and adjustment for covariates. To the best of our knowledge, this is the first study to empirically evaluate the health impacts of the coal-to-clean energy policy, though our results are supported by several risk assessments that estimated a range of reduced health impacts based on the modeled emissions reductions in shifting from coal-to-clean energy. One risk assessment estimated that, by 2030, the policy would avoid 0.78 million morbidities and 0.01 million deaths in the Beijing-Tianjin-Hebei region (241), and another study estimated a 32% reduction in premature deaths attributed to residential fuel burning in northern-China (242).

Only a small number of studies mostly conducted in high-income countries have empirically assessed the health impacts of household energy policies (45), with the majority indicating some level of health benefit. In Ireland, coal bans implemented in 1990s were associated with reductions in respiratory mortality in ban-affected counties compared with neighboring counties not affected by bans, though they did not observe reduction in cardiovascular mortality (146). A wood-burning stove exchange program in Central Launceston (Australia) was associated with lower wintertime cardiovascular (−19.6%) and respiratory (−27.9%) mortality in the intervention communities but not a nearby control city that did not participate in the program (147). In California's San Joaquin Valley Air, an air quality-dependent wood burning ban was associated with a decrease in cardiovascular (-7%) and specifically ischemic heart disease (-16%) hospitalizations in adults 65y+ but not in younger adults (148). A policy subsidizing LPG in Ecuador saw a 20% decrease in lower respiratory infection mortality in those under 5 yeads old (150).

Randomized trials of less polluting cookstoves further support the cardiovascular benefits of clean energy observed in our study. In Guatemala, a chimney stove intervention lowered exposure to air pollution and reduced the occurrence of nonspecific ST-segment depression in older women (243). That trial and others in Nigeria and Ghana observed reductions in blood pressure (-1.3 to -3.7 mmHg) in women assigned gas, ethanol, or improved combustion biomass stoves (244-246), and are supported by non-randomized intervention studies in Nicaragua and Bolivia (-1.5 to -5.5 mmHg lower mean systolic blood pressure in the intervention group) (247, 248). In contrast, a multi-country randomized trial observed small increases in gestational blood pressure (systolic/diastolic: 0.69/0.62 mmHg) in mothers assigned gas cookstoves (125), though mean participant age was younger (mean age: 25y) than the other intervention studies that showed cardiovascular benefit of intervention (mean ages: 28 to 53y).

We were unable to investigate the mechanisms though which the policy reduces AMI in this province-wide study. The introduction of a new heating stove likely has direct implications for indoor air pollution and indoor temperature, both of which are well-established risk factors for AMI (151, 249). A cross-sectional study in Beijing observed lower indoor air pollution (mean difference: 130 $\mu g/m^3$) and warmer indoor temperatures (mean difference: 1.4°C) in villages treated by the coal-to-clean energy policy compared with similar households in similar untreated villages located in the same region (141). Still, household energy is central to daily life, and it is possible that the policy could affect other mechanisms including behavioral change (e.g., physical activity and diet) that may impact incidence of AMI and forms a potential opportunity for investigation in future studies.

We observed larger effects of the policy on AMI events in older adults which is similar to previous findings in the San Joaquin Valley (U.S.) where the cardiovascular benefits of exposure to a wood-burning ban were limited to older adults (148). The larger effect in older residents of Beijing may be attributable to several factors. Older adults are at higher risk of experiencing an AMI event, which suggests they may also benefit more from interventions. Previous studies show that older adults are more likely to experience cardiovascular impacts of changes in temperature (250, 251) and air pollution, including in settings of household coal and biomass use (148, 252). Older adults are also more likely to stay at home during the day than younger adults (37), which would impact their exposure to a household heating intervention and any environmental, behavioral, or social benefits that it provides.

We also found consistently larger AMI benefits of the policy among women compared with men. This may be attributable to over twenty-fold higher rates of tobacco smoking among Chinese men versus women (50.8 and 1.9%, repectively) (253). This may mask the comparatively small air quality benefit of a new heater. In contrast with our results, a wood stove change-out in Australia was associated with reductions in cardiovascular mortality in men (−17.9%, 95%CI: −30.6, -2.8) but not women (147). Smoking rates for men and women in Australia are similar (13% and 11%, respectively) (254).

Reductions in AMI incidence were greater in townships that were considered as treated longer by the policy in our study. Studies of outdoor air pollution observed that long-term exposure to $PM_{2.5}$ over years can increase cardiovascular disease risk by an even larger magnitude than short-term exposures over days to months, suggesting that the cardiovascular benefits of intervention may accumulate over time (113). It is also possible that these time-varying effects are an artifact of our township-level treatment variable, where the percentage of villages treated in a township can only increase over time and the larger AMI benefits in townships treated longer may simply reflect the higher proportion of villages treated in those townships. For example, among townships considered treated by 2016-17 in our study, we observed a 5% annual average increase in the proportion of villages treated for the remaining two years of study. Additionally, use of 2-year rates starting in January meant AMI rates from the first period the townships were treated contained AMI events from before the townships was treated which would likely increase the AMI rates in the first treatment period.

Our DiD analysis is subject to several assumptions. Our analysis assumes that treatment by the policy is not differentially anticipated by those treated versus not. It was generally known that roll-out of the policy was starting in areas closer to the urban core with upgraded electricity grids and would then move into other plains regions and later into more mountainous areas.

Outside of those geographical parameters, some villages with sufficient existing infrastructure were assigned into the policy whereas others applied, but villages were generally unaware if and when they would be treated (141). We cannot entirely rule out the possibility that other policies may have differentially affected AMI rates by treatment group, which could lead to over-or under-estimation of the treatment effect. Beijing implemented numerous rural development (255) and air quality policies over the past two decades (241), though we are not aware of any policies that followed the same spatial distribution as the coal-to-clean energy policy. Finally, our analysis was based on the assumption that, in the absence of the policy, the trends in AMI incidence in our treated and untreated townships would have remained the same over time (i.e., parallel trends). We observed similar trends in AMI incidence in the pre-treatment period from 2007- 2014 and also conducted our analysis using a combination of regression adjustment and inverse probability weights, which improve the plausibility of the conditional parallel trend assumption holding true for townships with similar characteristics.

Our study has several limitations to consider for future analyses. First, the policy was implemented at the village-level, but we defined treatment at the township level to match the smallest available geographic resolution of AMI data for Beijing. Townships considered treated in our analysis (i.e. >50% of villages treated) thus included untreated villages and visa versa, which would most likely be non-differential misclassification of treatment and bias the effect of treatment towards the null. Applying a more conservative cut-off to define treated (>70% villages treated) and untreated (<30% villages treated) townships produced estimates that generally suggesting a larger impact on AMI rates. Second, spillover health benefits of the policy are also possible. A benefit of our township-level treatment variable is that it may capture some of the potential village-level spillover effects of the policy. Still, modeling studies indicate improved regional air quality from the policy whereby untreated townships could also experience air quality benefits of the policy (190), which would likely bias our results toward the null. Finally, our main analysis defined treatment status for the two-year calendar periods during which AMI rates were estimated, which likely introduces some misclassification in exposure. New heating stoves were typically installed between March and November, meaning that length of time treated differs across villages that joined the policy in the same calendar year. We assessed this potential bias by conducting models with two-year AMI rates estimated for November to October and, for older adults, with single-year AMI estimation, which yielded results showing an overall AMI benefit of the policy.

Conclusion

Household energy programs and policies are being scaled up in China and around the world due to widespread programmatic and policy efforts by governments and other organizations. Using data on AMI incidence and treatment by the policy in Beijing's rural and peri-urban townships, our results provide among the first empirical evidence of cardiovascular benefits attributable to a large-scale clean energy policy. Our results may help to motivate continued investment in clean energy in China and in other regions that are developing and implementing household energy policies.

Declaration of interests

We have no competing interests to declare.

Acknowledgments

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Data availability statement

The data used for this study were obtained from the Beijing Municipal Health Commission Information Center and cannot be shared publicly, given their institutional regulations and the data confidentiality agreement. Similar data may be requested by researchers from the above data holder authorities for research purposes. The analytical methods can be reproduced based on the details provided in this article, and the statistical code is available upon request.

5.3 Supplementary Information

1. *Determining township eligibility for treatment by the coal-to-clean energy policy*

Urban communities and villages in Beijing were ineligible for treatment by the coal-to-clean energy policy because they were already connected to district heating systems that supply heat from central locations. We did not have access to village-level data on centralized heating, and therefore needed to identify townships in which communities and villages were mostly connected to centralized heating and ineligible for the policy. We first excluded 151 townships in which the majority of their smallest administrative units with the urban designation of community (社区) which are usually connected to centralized heating and thus ineligible for treatment by the policy. We additionally excluded one township with an urban designation in its name (街道) rather than 镇 or 乡 and excluded four townships in the city center with less than 10% of villages and communities enrolled in the policy, suggesting that the majority of villages in those townships had centralized heating. Prior to categorizing a township as ineligible, we also visually assessed satellite images of the township for urban build (e.g., high rise apartment buildings) up that indicates access to centralized heating. In total, 156 of the 307 townships were considered ineligible and excluded from the main analysis.

2. *Age and sex-standardization of AMI incidence rates*

Age- and sex-standardized AMI incidence rates (AMI events per 100,000 population) were calculated by the direct standardization method using the Beijing population from the 2010 national population census as the reference. For the main analysis, age and sex categories for standardization included men and women aged 35 to 64 and ≥65 years with corresponding weights of 43.1% and 8.0% for the two age groups in men, and 39.8% and 9.1% for those in women, respectively.

3. *Geolocating villages treated by the coal-to-clean energy policy*

After excluding a small number of duplicate village entries (n=25), the 2519 villages listed as enrolled into the coal-to-clean energy policy by 2019 were matched with villages in a complete administrative dataset of villages obtained from the Chinese National Bureau of Statistics in 2019 (n = 7168) (203). We matched villages using their village, township and district names while considering similar names or alternative spellings in the same township or a neighboring township and by also searching Baidu Maps (202) and Baidu Baike (204). Ten of the 2519 villages treated by the policy were excluded from the dataset because they could not be identified in any townships (n=5) or were no longer independent administrative villages by 2019 (n=5) according to the National Bureau of Statistics (203). Nineteen villages listed as enrolled in the policy were not listed in the administrative villages and communities data but were added to our administrative dataset after identifying their location on Baidu Maps (202) and verify their existence on Baike (204). The final village dataset contained 7187 villages, of which 2519 were treated by the policy by 2019. Most villages (n=864) were listed as entering the policy in a single year, though others entered into the policy over a period of 2 (n = 718), 3 (n = 141), or 4 (n = 5) years. For this study we considered villages as treated by the policy in the first year of entry.

4. Covariate descriptions and data sources

Table of covariates definitions and sources

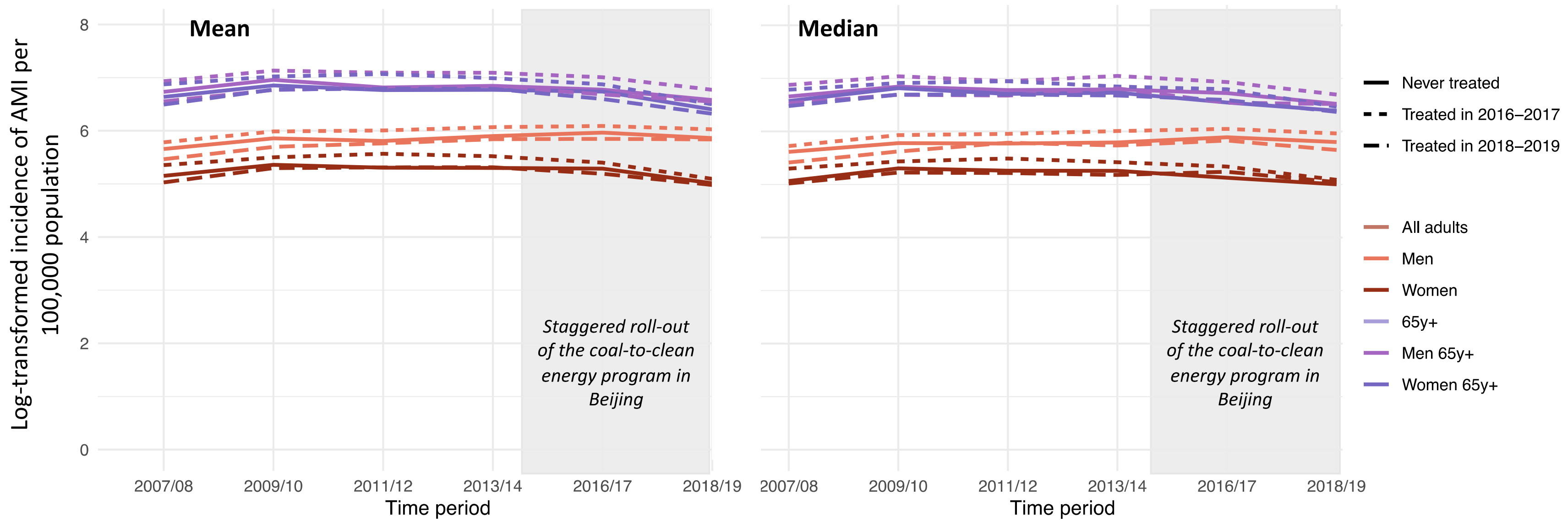
Covariates	Definition	Spatial resolution	Years with data available	Source
Population with secondary school education or higher (%)	Population with high school over higher educational attainment divided by the population ages 6y and older	Township	2010	2010 national population census (256)
Population working in agriculture (%)	Population working in agriculture and related industries minus those working in agricultural services (tertiary industry) divided by total population	Township		
Population unemployed (%)	Individuals ages 16 years and older who are not employed but able to and seeking work divided by the economically active population (population 16 years and older able and wanting to work)	District		

Population current smokers (%)	Current smokers were defined as individuals that currently smoke	District	2014 and 2017	Beijing Chronic Disease and Risk Factors Surveillance (257, 258)
Population with obesity (%)	Body mass index (BMI) ≥28kg/m^2			
Population with hypercholesterolemia (%)	Total cholesterol ≥6.22 mmol/L			
Access to health care	Number of secondary and tertiary hospital beds per 1000 population measured using an enhanced 2-step floating catchment area method based on a Gaussian function	Township	2013-2019	Chang et al. (2023) (259)
Outdoor temperature (°C)	Average outdoor temperature for the months of December, January, and February calculated from hourly temperature data	Township	2013-2019	ERA5 hourly data on single levels from 1940 to present (260)

Figure S1: Spatial distribution of the proportion of villages and communities in Beijing townships participating in the coal-to-clean energy policy by the end of A) 2017 and B) 2019

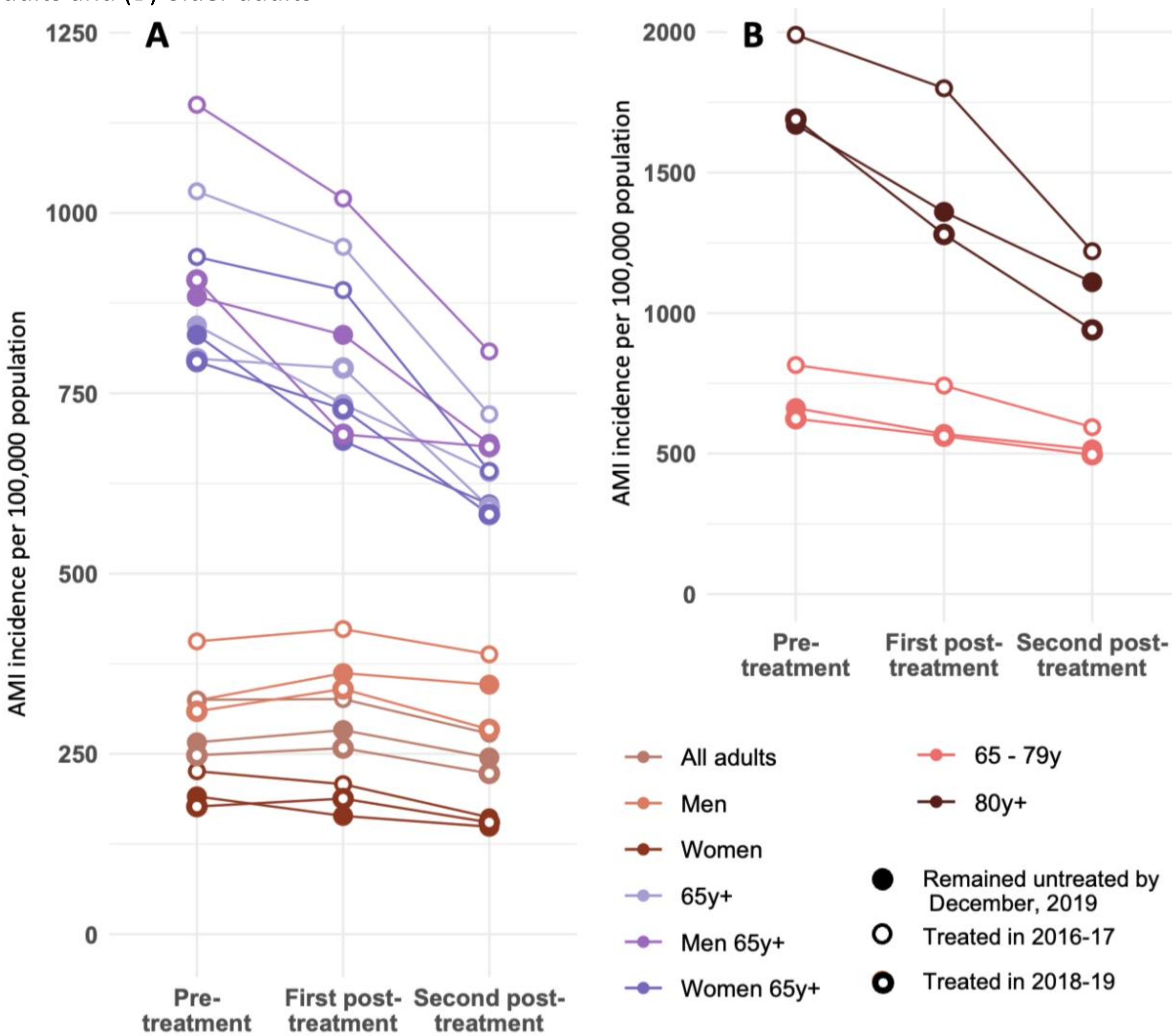
Note: Eligible townships were considered treated if more than 50% of villages and communities were participating in the policy. Townships comprised of mostly urban communities connected to central heating were considered ineligible for this study.

Figure S2: Temporal trends in mean and median of log-transformed incidence of acute myocardial infarction (AMI) among adults in eligible Beijing townships from 2007 to 2019



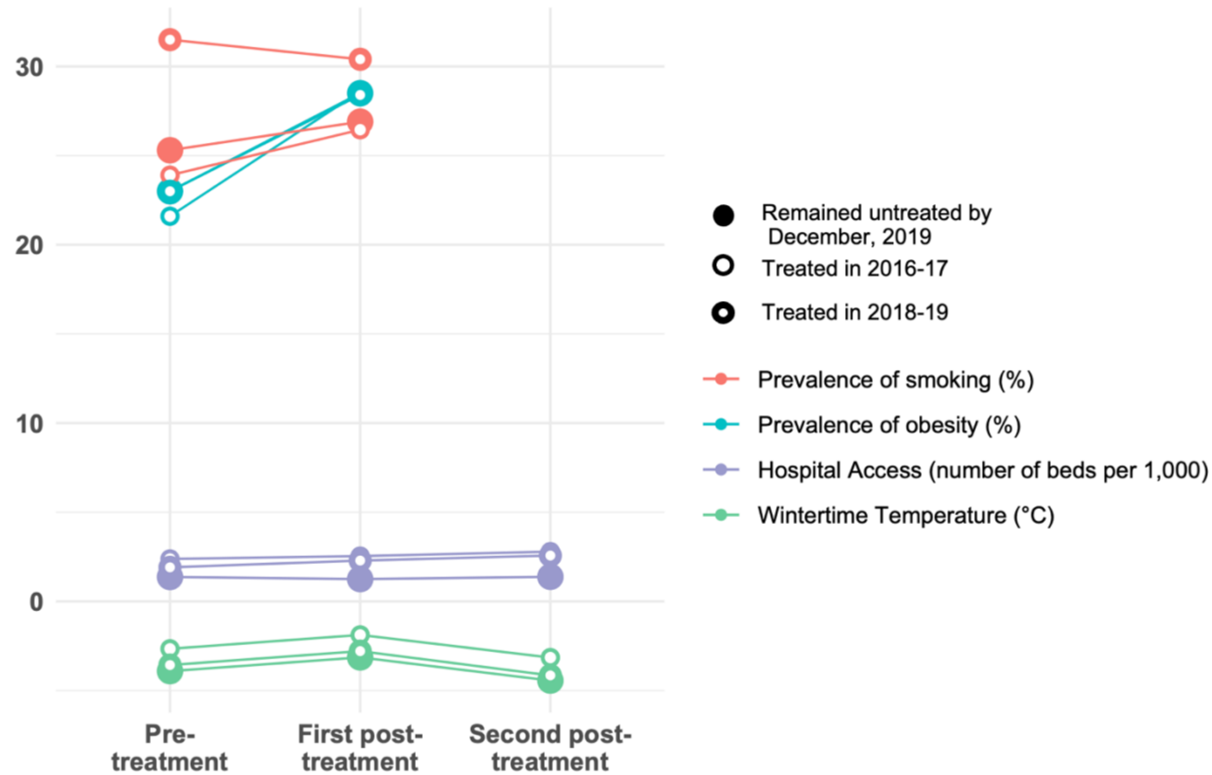
Note: Eligible townships were considered treated if more than 50% of villages and communities were participating in the policy. Townships comprised of mostly urban communities connected to central heating were considered ineligible for this study.

Figure S3: Temporal trends in median age-standardized incidence of acute myocardial infarction (AMI) for Beijing townships by sex and age-group and treatment group for (A) all adults and (B) older adults



Note: Townships were considered treated when more than 50% of village and communities in the township were participating in the coal-to-clean energy program in that time period.

Figure S4: Temporal trends in median outdoor temperature and access to health care in eligible Beijing townships. Township averages are presented for the pre- and post-treatment periods and by treatment group. Townships were considered treated when more than 50% of village and communities in the township were participating in the coal-to-clean energy program in that year



Note: Access to health care is estimated based on the number of hospital beds per 1,000 population. Outdoor temperature is averaged over the winter months (November – January). Values for the second post-treatment period for obesity and smoking prevalence were not included as they are the same and the first post-treatment period. We only had data from 2017 for the post-treatment period.

Table S1: Township characteristics (mean and standard deviation) in the pre-treatment period (2013-2014), by treatment group

Characteristic	Untreated (n=59)	Treated in 2016-2017 (n=75)	Treated in 2018-2019 (n=17)
Incidence of acute myocardial infarction (events per 100,000 pop)			
All adults	286 (88.9)	344 (97.3)	276 (98.4)
Men	366 (130)	432 (125)	344 (109)
Women	201 (60.0)	250 (80.2)	203 (92.4)
Adults 65y+	904 (278)	1140 (381)	909 (339)
Men 65y+	939 (296)	1200 (392)	931 (298)
Women 65y+	872 (297)	1090 (406)	889 (411)
Population working in agriculture (%)	75.7 (17.4)	76.1 (9.7)	72.4 (14.5)
Population unemployed (%)	4.8 (1.6)	4.3 (0.9)	4.3 (0.5)
Population with high school education or higher (%)	25.7 (10.2)	28.7 (6.5)	33.6 (12.1)
Population current smokers (%)	29.6 (9.2)	25.9 (6.9)	30.6 (11.0)
Population with obesity (%)	24.4 (4.8)	22.4 (4.6)	23.4 (4.0)
Access to health care (number of hospital beds per 1000 population)	1.9 (1.8)	2.5 (1.0)	2.2 (1.2)
Average ambient temperature in the heating season (°C)	-4.1 (1.5)	-2.9 (0.9)	-4.2 (1.5)
Population with hypercholesterolemia (%)	6.8 (2.6)	7.3 (1.9)	7.0 (2.4)

Note: A township was considered treated if more than 50% of its villages and communities were participating in the coal-to-clean energy policy. Means and standard deviations of township AMI incidence and covariates are provided in Table S1. Obesity was defined as having a BMI ≥28kg/m^2. Access to health care was defined based on the number of secondary and tertiary hospital beds per 1000 population. Heating season refers to the months of December, January, and February. Hypercholesterolemia was defined as total cholesterol ≥6.22 mmol/L.

Figure S5: Histograms of all 6000 lower 95% CI estimates of average treatment effect on the treated (ATT) per 100,000 population generated from the 6000 runs of the multiple time point different-in-difference used to generate the confidence intervals for the main analysis

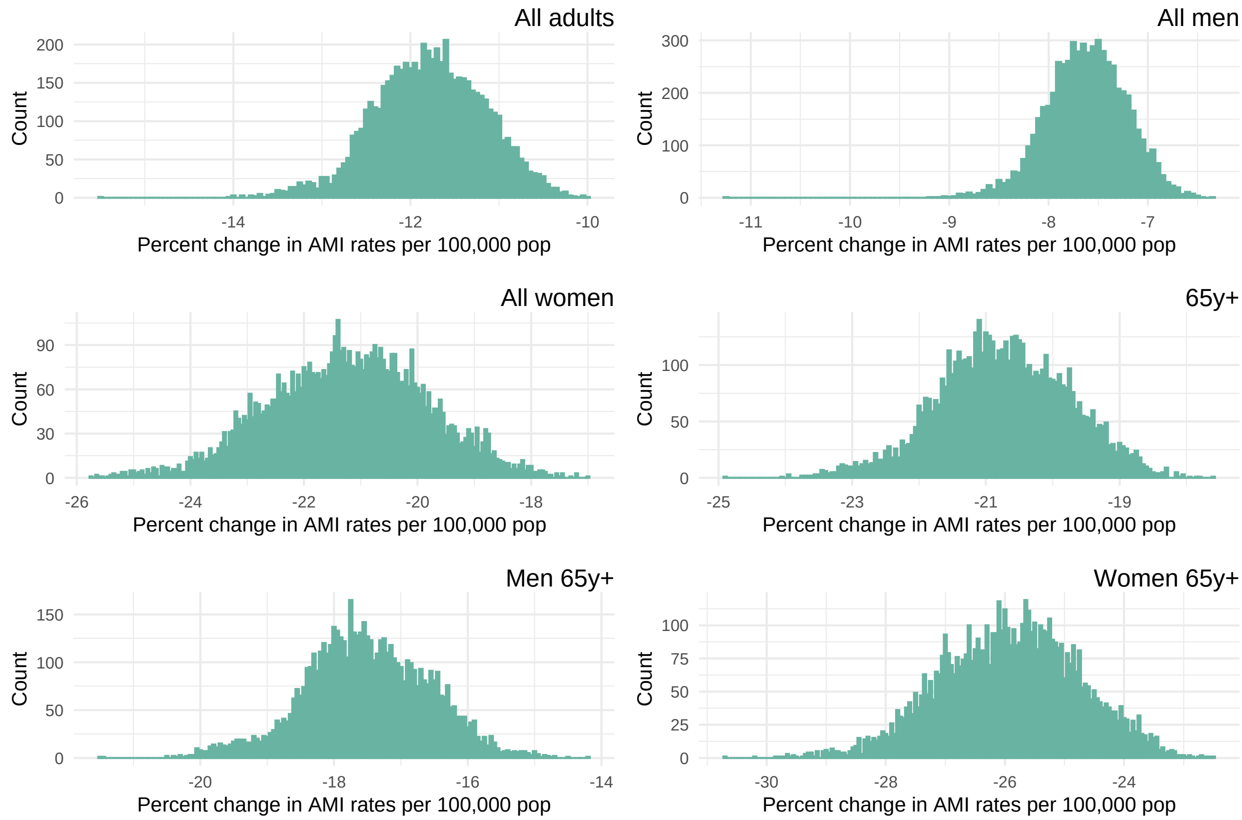


Figure S6: Histograms of all 6000 upper 95% CI estimates of average treatment effect on the treated (ATT) per 100,000 population generated from the 6000 runs of the multiple time point different-in-difference used to generate the confidence intervals for the main analysis

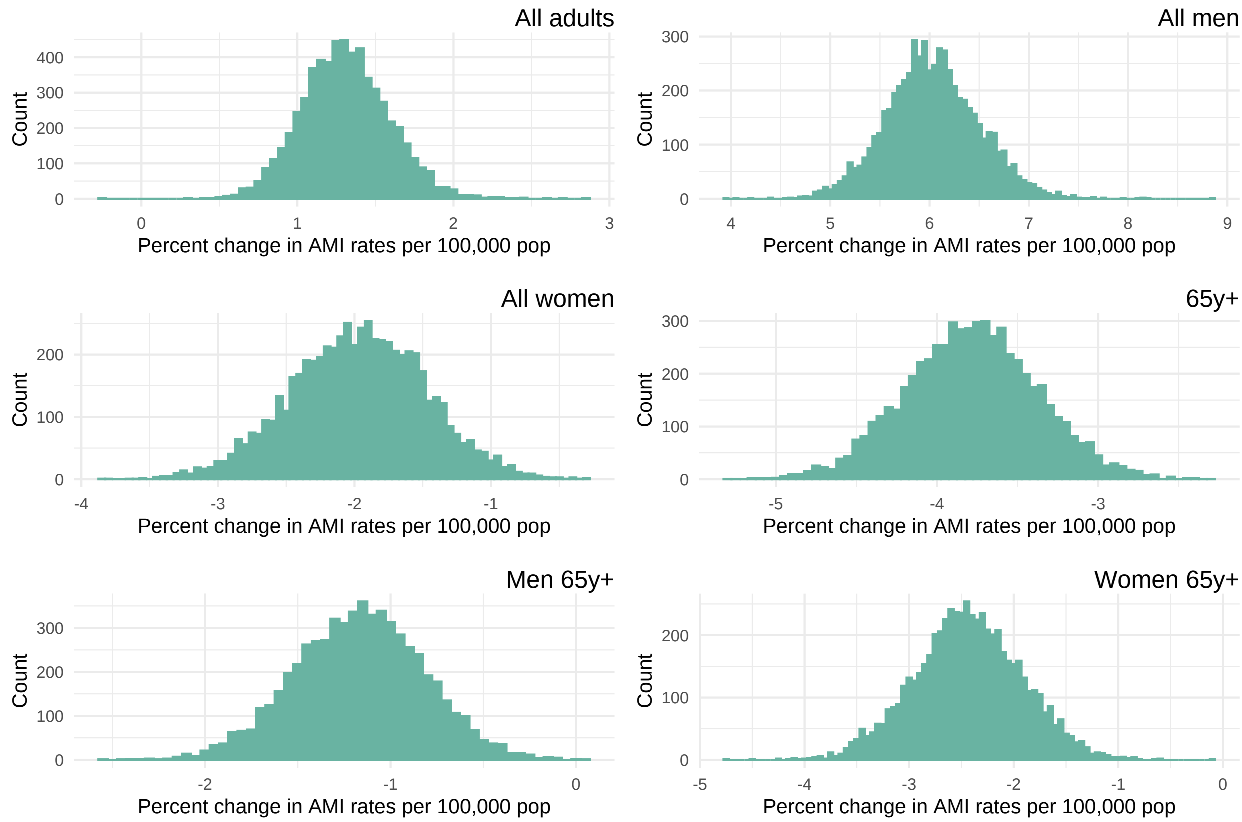


Table S2: Average treatment effect on the treated (ATT) of the clean energy program on acute myocardial infarction (AMI) incidence (events per 100,000) in Beijing townships [with 95% confidence intervals]: results from a staggered difference-in-difference analysis adjusted for covariates

Age-group and sex category	Results from the main analysis	Two-year AMI rates estimated for Nov to Oct	1-year AMI rates	Two-year AMI rates standardized using four age groups (35-49y, 50-64y, 65-79y, and 80y+)	Excluding two outlier townships	Treatment defined as >70% of villages in the townships treated by the policy. Untreated is defined as <30%	Removal of potentially ineligible townships	Including hypercholesterolemia as covariate
All adults	**-5.5 [-11.8, 1.3]**	-5.7 [-11.1, -0.2]	-	-6.1 [-12.4, 0.6]	-5.6 [-11.9, 1.1]	-7.1 [-16.1, 2.6]	-4.6 [-12.3, 3.5]	-7.0 [-13.2, -0.5]
Men	**-1.1 [-7.6, 6.0]**	-3.1 [-8.9, 3.3]	-	-	-1.3 [-7.7, 5.7]	-2.8 [-12.8, 8.2]	-1.7 [-10.8, 8.3]	-2.2 [-8.7, 4.8]
Women	**-12.1 [-21.2, -2.0]**	-8.9 [-18.1, 1.6]	-	-	-12.1 [-21.3, -1.9]	-13.4 [-25.8, 1.0]	-6.7 [-15.1, 2.4]	-14.4 [-22.9, -5.1]
65y+	**-12.6 [-20.8, -3.8]**	-10.1 [-17.9, -1.6]	-6.0 [-15.2, 4.1]	12.5 [20.6, -3.7]	-12.6 [-20.9, -3.8]	-14.5 [-25.6, -2.2]	-10.7 [-18.8, -2.1]	-14.3 [-22.1, -6.0]
Men 65y+	**-9.6 [-17.5, -1.2]**	-8.7 [-16.8, 0.3]	-3.3 [-13.4, 8.2]	-	-9.6 [-17.4, -1.2]	-14.8 [-25.2, -3.8]	-9.3 [-18.1, 0.0]	-10.4 [-18.2, -2.2]
Women 65y+	**-14.9 [-25.9, -2.4]**	-11.2 [-22.3, 1.7]	-7.8 [-18.3, 3.7]	-	-15.1 [-26.2, -2.4]	-13.3 [-29.2, 5.8]	-10.7 [-20.9, 0.5]	-17.6 [-27.7, -6.2]
65-79y	**-10.4 [-19.0, -1.0]**	-	-	-	-10.4 [-18.9, -1.1]	-15.2 [-27.1, -2.2]	-9.0 [-18.4, 1.2]	-12.4 [-20.7, -3.5]
80y+	**-13.3 [-25.1, 0.0]**	-	-	-	-13.3 [-25.2, 0.2]	-10.9 [-28.4, 10.8]	-10.6 [-23.2, 3.9]	-14.7 [-26.0, -2.0]

Note: Townships considered treated when more than 50% of villages and communities in the township were treated by the policy. Effect estimates are presented as the percent change in AMI, calculated as (exp(coef)-1)*100 to account for log transformed AMI rates.

Chapter 6: Discussion

6.1 Summary of Findings

This thesis examined the impacts of household solid fuel use on exposure to air pollution, and assessed whether a real-world policy aimed at reducing solid fuel use and promoting clean energy transition can provide air quality and health benefits. My thesis adds to the current literature by using novel field data to describe the levels and variability in exposures to air pollution in a complex air pollution exposure setting and assessing the explanatory contributions of indoor and outdoor sources to variability and levels of personal exposures. It also provides among of the first empirical assessments of the air quality and health impacts of a large-scale clean energy policy.

Objective 1 (Chapter 3) of the thesis focused on the measurement and modelling of personal exposure of $PM_{2.5}$ and black carbon in older Chinese adults in three provinces in China, with an aim of estimating 'usual exposure' using repeated measurements of air pollution across seasons. The study benefited from over 48,000 hours of measurement of personal exposure to $PM_{2.5}$ and black carbon from 787 men and women (ages 40-79) in northern (Beijing and Shanxi) and southern (Guangxi) China. I found that personal exposures to $PM_{2.5}$ across all seasons and study sites were, on average, higher than the World Health Organization's (WHO) 24-h $PM_{2.5}$ Air Quality Guideline and exceeded the relatively high levels of outdoor $PM_{2.5}$. The repeated measures in this study show that within-individual variance, relative to between-individual variability, dominated the total variability in exposures across all study sites, genders, and seasons. In future epidemiologic and intervention studies, repeated daily measurements of exposure are likely needed to capture 'usual' daily exposure in these settings, even within a single season. My results also indicate that measurably reducing air pollution exposures in these study settings will likely require reductions in emissions from both indoor and outdoor sources, which are linked to different mitigation strategies.

In Objective 2 (Chapter 4), I moved from an individual-level to small area-level analysis to assess whether exposure to the coal-to-clean energy policy in Beijing was associated with changes in local outdoor satellite-derived $PM_{2.5}$. In this study, I did not find an association between satellite-derived $PM_{2.5}$ and exposure to the policy in Beijing. It is possible that an indoor intervention like a new heating stove has little measurable effect on ambient $PM_{2.5}$. This combined with spillover effects from areas not exposed to the policy, continued use of coal stoves, and other air pollution sources could also mask the air quality benefits of the policy. Further, the satellite-derived $PM_{2.5}$ data used in this study are spatially smoothed and limit our ability to accurately measure local $PM_{2.5}$. This may limit my ability to observe local changes over time, especially since other environmental policies were simultaneously implemented in Beijing during the same time period.

For Objective 3 (Chapter 5), I conducted a township-level analysis and estimated the effect of the coal-to-clean energy policy on the incidence of acute myocardial infarction (AMI) in Beijing between 2013 and 2019. This study is among the first to empirically examine the relationship of a large-scale clean household energy policy and cardiovascular disease. There was an observed reduction in AMI incidence in Beijing townships treated by the coal-to-clean energy policy compared with untreated townships. The effects were largest in women and older adults (65y+), which is the age group most susceptible to AMI. Our results were robust to multiple sensitivity analyses and may help to motivate continued investment in clean energy in China and in other regions that are developing and implementing household energy policies.

6.2 Strengths and Limitations

This thesis has a number of strengths compared with the previous studies on these topics. All three objectives make important **substantive contributions** to the field of epidemiology and household energy policy by filling important knowledge gaps which were identified as priority research areas by international organizations like the Health Effects Institute and the U.S. Environmental Protection Agency, and by numerous systematic and scoping reviews (17, 44, 261-263).

Objective 1 examines an important assumption about representativeness of short-term (24- or 48-hour) measurement of personal exposure to $PM_{2.5}$, which has been the commonly used as the exposure measurement in studies of household air pollution as a surrogate of 'usual' long-term exposure (44). Despite the considerable practical and logistical challenges of conducting large panel studies of exposure in rural and remote study settings (183), we collected up to four days of exposure measurements for a large group of participants which allowed me to evaluate both the within-individual and between-individual variability in exposure. My study was one of the first to assess personal exposures and its determinants in men in a setting of household air pollution, showing that their exposures were similar to women after accounting for smoking. Policy organizations and global and national risk assessments, including those conducted by the WHO (177), have generally assumed that men including those in China experience lower exposure to household air pollution than women due to traditional gender roles around cooking. My study contributes to the very limited evidence on exposure among men (264, 265), and can used to inform future epidemiologic studies and risk assessments, especially those that include China.

Objectives 2 and 3 fill important empirical knowledge gaps about the impacts of clean energy policies on local outdoor air quality and health. Most previous studies use risk assessments that model the air quality and health benefits based on the estimated or predicted changes in air pollution emissions from a policy or intervention. Impact assessments like mine can be especially useful for exposure science or epidemiology as they can provide direct evidence of the effectiveness of an intervention and are the closest 'real world' alternative to a controlled experimental study. Further strengths are my population-based assessment of a large-scale energy policy, Chapter 5, using a quasi-experimental design, and adjustment for covariates.

My thesis also has a number of **methodological strengths.** In Objective 1, key strengths include gold-standard (gravimetric) measurement of personal exposure to $PM_{2.5}$ for up to four days and across two seasons (over 48,000 hours of measurements). I also obtained measurements of outdoor $PM_{2.5}$ and many important environmental, housing, and socio-demographic variables for 787 adults from three geographically diverse provinces in China. Another strength of this study was the photo-based assessment of household fuel use at the time of survey and in the previous 20 years. By capturing all stoves and fuels used, the study's exposure variable is less prone to measurement error than the more commonly use metric of 'primary fuel' type. This metric does not adequately capture the complexity of modern-day energy environments where use of multiple stoves and fuels is needed to meet the diversity of household energy tasks. These detailed field data and repeated measures enabled me to implement mixed effects models to estimate the within- and between-participant variance components of personal exposure and to assess the determinants of exposures.

In Objective 2, I was able to leverage high-resolution geospatial data on air pollution, exposure to the residential coal-to-clean energy policy, and other local land-use and meteorological conditions for all of Beijing to evaluate whether exposure to the policy impacted local satellite-derived $PM_{2.5}$. The spatial attributes of these data allowed me to empirically estimate the associations at the small-area level. Previous studies were limited to district-level analyses or risk assessments (190, 230). My study additionally accounted for spatial autocorrelation in $PM_{2.5}$. Though I did not observe an effect of the policy on $PM_{2.5}$, my approach and methods can be used in future studies on these topics.

The largest methodological strength of Objective 3 is my quasi-experimental design which provides stronger casual evidence of the impacts of the coal-to-clean energy policy on AMI, assuming that our model assumptions are met (e.g., parallel trends in outcomes between treatment groups in the absence of treatment; treated townships remain treated over time). The staggered rollout of the policy over time combined with use of a multiple timepoint DiD approach allowed me to examine the cardiovascular effects of shorter versus longer-term exposure to the policy. Further, while use of a DID analysis should reduce the potential impact of time-invariant confounders, I also selected a methodological approach that accounts for differences in covariates by treatment groups (266). Another strength of my study is the inclusion of all townships in rural and peri-urban Beijing, thus capturing the range of income levels and economic development across the province. Finally, through a collaboration with Anzhen hospital in Beijing, I obtained small-area (township) estimates of AMI incidence for over a decade, the smallest spatial resolution available, which are collected through a world-class cardiovascular disease surveillance system.

My thesis also has a number of limitations that can be considered in the design and implementation of future studies on these topics.

In Objective 1, I was unable to account for differences in time-activity patterns (e.g., via global positioning systems (GPS)) which are likely important determinants of exposure. To avoid excessive participant burden, we were also limited measurement to two days per season which, while longer than previous studies, limited our ability to accurately assess long-term personal exposure. This limitation is further supported by our results showing large and mostly unexplained within-individual variability in exposure. Newer sensors like the Ultrasonic Personal Air Sampler (UPAS) (267) include GPS and are lightweight and virtually silent but were not available at the time of data collection for this study. It is possible that some participants may have altered their daily activity patterns due to wearing the monitors or attending clinic visits which could bias our estimates of their 'usual' exposure. It is difficult to anticipate the direction of such potential bias. Cooking and heating with solid fuel are generally core features to daily life and not viewed as socially undesirable, which makes it less likely that participants would intentionally reduce their exposures because of sampling.

In Objective 2 one of the main limitations is our use of satellite-derived estimates of $PM_{2.5}$ as our air quality outcome. This data allowed us to capture air quality for all of Beijing but likely introduced considerable measurement error. Satellite-derived data are less likely to capture the local air quality impacts of a household-level intervention than indoor- or village level field measurements. The error is most likely independent of exposure to the policy and would increase our standard errors. My study is also subject to misclassification in small area-level exposure to the policy. I estimated exposure at the ~1km × 1km grid cell level using a geolocated list of villages, where each village was spatially allocated as a coordinate point to a single grid cell, though the exact geographic boundaries of villages were unknown. Likely the geographic boundaries of some villages spanned more than one grid-cell. Spillover effects of the air pollution policy are also possible but challenging to statistically account for in the analysis. Areas without villages enrolled in the policy could have benefited from reductions in local air pollution from upwind villages exposed to the policy. I attempted to account for these spatial spillover effects by choosing a spatiotemporal model that accounts for spatial autocorrelation by modeling spatial random effects using Gaussian Markov random fields within the SPDE framework. Though, while this method is effective for capturing spatial dependencies, it may not completely capture spatial spillover.

In Objective 3 my approach to estimating the casual effects of the coal-to-clean energy policy on AMI incidence relies on a set of strong and largely unverifiable assumptions. Though these are not necessarily limitations of my study, it is important to nonetheless evaluate the likelihood that these assumptions hold for my analysis. Perhaps most importantly, I assumed that the AMI outcomes of the treated and untreated groups would have evolved similarly over time in the absence of the policy. Supporting this assumption is that I observed similar trends in AMI rates in the pretreatment period between treatment groups. I also implemented a doubly robust estimation which specifies the DiD regression models for both the outcome and the treatment as a function of covariates. Second, I could not entirely rule out the possibility that other policies may have differentially affected AMI rates by treatment group, which could lead to over-or under-estimation of the treatment effect. Beijing implemented numerous rural development (255) and air quality policies (139) over the past two decades that could in theory also impact cardiovascular health (241), though my collaborators and I am not aware of any policies that followed the same spatial distribution as the coal-to-clean energy policy.

Objective 3 has several limitations to consider for future analyses. First, the policy was implemented at the village-level, but I defined treatment at the township-level to match the smallest available geographic resolution of AMI data for Beijing. Townships considered treated in the analysis (i.e. >50% of villages treated) thus included untreated villages and visa versa, which would most likely be non-differential misclassification of treatment and bias my estimates towards the null. This is supported by results from my sensitivity analysis where applying a more conservative cut-off to define treated townships (>70% villages treated) and untreated townships (<30% villages treated) produced estimates that suggest an even larger benefit of the policy on AMI incidence. Second, spillover health benefits of the policy are also possible. A benefit of our township-level treatment variable is that it may capture some of the potential village-level spillover effects of the policy. Still, modeling studies indicate improved regional air quality from the policy whereby untreated townships could also experience air quality benefits of the policy (190), which would likely bias our results toward the null. Finally, the main analysis defined treatment status for the two-year calendar periods during which AMI rates were estimated, which likely introduces some misclassification in exposure. New heating stoves were typically installed between March and November, meaning that AMI incidence rates included events from villages before they were treated. I assessed this potential bias by conducting models with two-year AMI rates estimated for November to October and, for older adults, with single-year AMI estimation, which overall yielded similar results showing an overall AMI benefit of the policy.

6.3 Epidemiology Significance and Policy Relevance

Household air pollution from solid fuel burning is a significant global health risk factor, especially in low-and middle-income countries (LMICs) which also experience some of the highest global levels of outdoor air pollution (1). Yet household air pollution remains woefully understudied compared with outdoor air pollution in high-income countries despite comprising a much larger portion of the estimated global burden of disease (44, 268, 269). As described in Chapter 2 and in the individual objectives, key knowledge gaps in the field are the limited understanding of how to best measure exposure for epidemiologic and intervention studies and the very few empirical studies that assess the air quality and health impacts of real-world clean energy policies. This thesis aims to directly address both knowledge gaps.

There are also several important policy contexts that motivated my thesis. First, the important role of clean energy access in development is recognized as a priority area in the Sustainable Development Goal 7 (SDG-7)) which aim to "ensure access to affordable, reliable, sustainable and modern energy for all' by 2030 (270, 271). Yet the 2019 SDG 7 tracking report indicated that global progress on transitioning to clean energy has been too slow, with an estimated 2.2 billion people predicted to still primarily rely on solid fuel energy by the target year even when just considering cooking (271). Most previous clean energy programs were limited to hundreds or several thousands of homes (67) and it is increasingly recognized that ambitious and large-scale clean energy policies like the coal-to-clean energy program are required to achieve SDG-7. Studies like my Objectives 2 and 3 that assess the air quality and health impacts of clean energy policies can be used to inform and possibly motivate future policies and programs.

Second, air pollution is recognized as global risk factor resulting in millions of premature deaths per year (1), and reducing exposures to air pollution, both outdoor and household, is a policy priority for many nations, including China (139). Air quality policies in China and other countries are implemented with the primary goal of improving population health but the limited knowledge of the determinants of exposure and the effectiveness of past policies in achieving their air pollution goals form a barrier to intervention design and development. My studies fill these evidence gaps by providing evidence on the levels and determinants of personal exposures to air pollution in settings where residential solid fuel burning is common and by evaluating the air quality and health impacts of a real-world clean energy policy that was implemented in millions of households in China.

Finally, in 2016, the Chinese government approved the Healthy China 2030 plan (*jiànkāng zhōngguó 2030*), the first long-term health planning document that represented an ideological shift from focusing mostly on economic development to a "health-centered coordinated development of economy and ecology" (272). Cardiovascular disease is the leading cause of death in China and increasing with population aging (224), making the prevention of cardiovascular disease vital to achieving this plan. My thesis results provide among the first empirical evidence of cardiovascular benefits from investment in clean heating energy policy and may help to motivate continued process in clean energy transition in China and in other regions that are developing and implementing household energy policies.

6.4 Future Research

Household air pollution and energy policy are large and interdisciplinary fields with multiple areas for further research that are relevant to improving environmental quality and population health. Given the high within-individual variability in daily personal exposure to $PM_{2.5}$ that I observed in Objective 1, my research calls into question whether the current standard of practice of 24-48h measurement of exposure can sufficiently capture long-term ‘usual’ exposure. A follow-up question is whether a combination of long-term household (indoor) and outdoor measurement might be combined to more accurately measure long-term exposure. At the time of data collection for Objective 1, a single air monitor ranged in cost from $750 to $3000 which limited the ability to conduct many long-term measurements in homes and villages. However, the emergence of high-performing low-cost air pollution sensors over the last decade provides new opportunities for larger-scale measurement campaigns. To better measure the impact of the clean energy policy on air pollution, for example, future studies could leverage low-cost sensing technologies to conduct measurements in homes and communities at a larger-scale than what was previously possible. These could be combined with data from ground-level monitors, when available, and satellite-derived air quality to more comprehensively measure air pollution.

In Objective 3, I conducted my analysis at the township level because this was the smallest resolution available. Village data are theoretically collected by the Beijing Cardiovascular Disease Surveillance System but were not available at the time of this study. Future research could assess the accuracy and completion of village-level information for AMI hospitalizations and deaths and re-conduct this analysis using village-level treatment. A further analysis would be to differentiate between fatal versus non-fatal AMI, which we were unable to do in this analysis because the smaller number of fatal AMI cases resulted in unstable township-level estimates. Further, field studies could be used to investigate the potential mechanisms though which the coal-to-clean energy policy impacted AMI rates, including possible changes in air pollution, indoor temperature or other behavioral changes with the introduction of a new heating technology.

Finally, future studies could leverage the measurements and methods used in this study to assess the air quality and health impacts other large-scale clean energy policies, for example the expansion of LPG in rural India (128, 273, 274), or Rwanda's Energy Sector Strategic Plan which includes plans to provide electricity to over 2 million households and provide clean cooking options (128, 135).

6.5 Conclusion

Household energy programs and policies are being scaled up in China and globally due to widespread efforts by governments and other organizations (128). Overall, this thesis provides a more nuanced understanding of the indoor and outdoor source contributors to personal exposures in settings of household solid fuel burning which can inform the design and development of interventions but also sets more realistic expectations of the air quality benefits that are achievable with a single, source-specific intervention in complex air pollution settings. My study provides empirical evidence of cardiovascular benefits from a large-scale clean energy policy in a place with a large and growing cardiovascular disease burden, though I did not observe local outdoor air quality impacts of the same policy. Together, these results may help to motivate continued investment in clean energy in China and in other regions that are developing and implementing household energy policies and provide a blueprint for the evaluation of clean energy policies on air quality and health.

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