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ABSTRACT

The Effect of Air Pollution on Body Weight and Obesity: Evidence from China*

We provide the first study estimating the causal effect of air pollution on body weight. Using the China Health and Nutrition Survey, which provides detailed longitudinal health and socioeconomic information for 13,226 adult individuals over 1989-2011, we find significant positive effects of air pollution, instrumented by thermal inversions, on body mass index (BMI). Specifically, a 1 μg/m3 (1.59%) increase in average PM2.5 concentrations in the past 12 months increases BMI by 0.31%, and further increases the overweight and obesity rates by 0.89 and 0.19 percentage points, respectively. Our paper identifies a new cause of obesity, and sheds new light on the morbidity cost of air pollution.

JEL Classification: I12, I15, Q53

Keywords: weight gain, obesity, air pollution, China

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1 Introduction

The last decades have seen an unprecedented increase in the fraction of population with body weight issues worldwide. In 2016, nearly 40% of adults were overweight (body mass index (BMI)>=25), while 11% of men and 15% of women worldwide were obese (BMI>=30) (WHO, 2018a). By contrast, the obesity rate in 1975 was only 3.2% for men and 6.4% for women (NCD-RisC, 2016). Overweight and obesity are important risk factors for a variety of chronic diseases, including diabetes, cardiovascular and kidney diseases, and some cancers (WHO, 2018a). It is estimated that overweight and obesity lead to at least 2.8 million deaths and 35.8 million disability-adjusted life years annually across the world (WHO, 2018b), and amounted to 2.8% of the global GDP in 2014 (Dobbs et al., 2014).

In response to this epidemic, numerous studies have sought to understand the complex and varied causes of obesity[1]. In this paper, we identify a new and important determinant of obesity: ambient air pollution, and particularly, very fine particulate matter ($PM_{2.5}$)[2]. At present, over 90% of the global population live in places with poor air quality. Understanding the link between air pollution and obesity is thus crucial for policy makers. To our best knowledge, this study is the first to estimate the causal effect of air pollution on BMI and obesity[3].

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[1] The majority of these studies have focused on the U.S., which currently has nearly 40% obese adults (Hales et al., 2018).

[2] We measure ambient air pollution using $PM_{2.5}$. Therefore, we use two terms interchangeably throughout this paper.

[3] Several studies in the health science literature find correlations between air pollution and obesity.

Our focus on China provides a unique opportunity to study the relationship between air pollution and obesity. Over the past decades, China's GDP has increased from USD 800 billion in 1989 to USD 6.7 trillion in 2011. Meanwhile, the national average concentration of $PM_{2.5}$ increased from 40.1 μg/m^3 to 68.4 μg/m^3 (Panel A of Figure 1). In the same period, the prevalence of overweight and obesity has also increased rapidly. The average BMI increased by 11%, while overweight and obesity rates increased from 8.57% to 32.83% and from 0.48% to 4.90%, respectively (Panels B–D of Figure 1). In 2014, China ranked first in obese men (16.3% of global obesity) and women (12.4% of global obesity) (NCD RisC, 2016).

Air pollution can affect body weight through the biological channel (e.g., slowing down the metabolism) and behavior channels (e.g., reducing exercise and increasing sedentary activities)[4]. Although previous studies have suggested multiple potential pathways between air pollution exposure and body weight, identifying the causal effect is challenging primarily because of the potentially omitted-variable bias. Air pollution is a byproduct of economic activity, and typically correlated with economic confounders, such as income and food prices, which are also important determinants of obesity (Cawley, 2015).

To identify the causal effect of air pollution on body weight, we use thermal inversions as an instrumental variable for air pollution. Thermal inversions occur when the temperature in the upper atmospheric layer is higher than that of the lower layer, thereby trapping air pollution near the surface. The formation of thermal

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See the review in An et al. (2018b).

[4] See detailed discussion in Section 2.

inversions is a complex meteorological phenomenon and typically independent of economic activities. Importantly, we utilize the longitudinal structure of our health data and include individual fixed effects. Therefore, our identification is from the fluctuation in air pollution instrumented by arguably exogenous thermal inversions across different years for the same individual. In addition, we include weather controls in flexible specifications and year-by-month fixed effects to control for seasonality in environmental and economic conditions.

Our data on body weight and height are from the China Health and Nutrition Survey (CHNS), which is the longest and most comprehensive health survey in China. The CHNS provided detailed information on health and nutrition along with socioeconomic and demographic data for 13,226 adult individuals (aged 18 or older) from eight provinces in China over the period of 1989–2011. Notably, the body weight and height, which are used to define BMI, are recorded by survey enumerators instead of being self-reported and are subject to measurement error bias. We then match the CHNS data with satellite-based pollution and thermal inversion data by county of residence and month of the interview for each interviewee.

Using a two-stage least squares (2SLS) estimator, we find significantly positive effects of $PM_{2.5}$ on body weight. Specifically, a 1 $\mu g/m^3$ (1.59%) increase in average $PM_{2.5}$ concentrations in the past 12 months increases BMI by 0.31%, and increases the overweight and obesity rates by 0.89 and 0.19 percentage points, respectively. The dynamics of exposure to air pollution matter: we do not detect significant short-run effects, such as the past one to three months, of $PM_{2.5}$ on body weight.

We then conduct a comprehensive heterogeneity analysis, and find similar effects between males and females, as well as urban and rural residents. However, we find a larger effect on adults aged below 60 and more educated population. Finally, we use more limited data to study the effect of pollution on behavioral responses including physical and sedentary activities, sleeping, and nutrition intake. However, we do not find any meaningful effects of these behavior responses because the survey only recorded these responses in a short window period, such as the past three or seven days before the interview.

This paper contributes to two strands of the literature. First, a growing body of literature seeks to understand the economic causes of obesity (Cawley, 2015). Most previous studies have focused on economic factors, including proximity to fast food outlets (Currie et al., 2010; Anderson and Matsa, 2011), income (Cawley et al., 2010; Akee et al., 2013), education (Brunello et al., 2013; Clark and Royer, 2013), and peer and neighborhood effects (Kling et al., 2007; Carrell et al., 2011). We show that the environment, particularly ambient air pollution, also plays an important role in causing obesity. For example, a 1 $\mu g/m^3$ increase in $PM_{2.5}$ has the same effect on obesity as an additional fast food restaurant and half of an additional year of schooling.

Our paper also contributes to the literature on estimating the cost of air pollution on a variety of economic outcomes, including mortality and morbidity

(Chay and Greenstone, 2003; Schlenker and Walker, 2015), labor productivity (Graff Zivin and Neidell, 2012), labor supply (Hanna and Oliva, 2015), and test scores (Ebenstein et al., 2016). We estimate that 1 μg/m^3 increase in average $PM_{2.5}$ concentrations induces a total of CNY 2.05 billion (USD 0.31 billion) health expenditure on overweight and obesity.

2 Mechanisms

Air pollution can affect body weight through several channels. First, air pollution could lead to metabolic disorder, which is closely related to body weight (An et al., 2018a). For example, Xu et al. (2011) find that $PM_{2.5}$ exposure triggers oxidative stress and adipose tissue inflammation, which further predispose to metabolic dysfunction. Toledo-Corral et al. (2018) find that $PM_{2.5}$ exposure has negative effect on glucose metabolism.

Second, air pollution could affect body weight indirectly through elevating the risks for a number of chronic diseases (An et al., 2018a). For example, air pollution exposure could lead to cardiovascular and respiratory diseases, heart diseases, and some cancers (WHO, 2018c). Consequently, these chronic diseases, could affect body weight (An et al., 2018a).

Third, air pollution could affect body weight through sleep disorders. Researchers have found that increased concentrations of PM significantly increase sleep disorders for adults in the U.S. (Zanobetti et al., 2009) and children in China (Lawrence et al., 2018). Sleep disorders, in turn, could increase BMI because of decreased leptin, thyroid-stimulating hormone secretion, and glucose tolerance, as well as increased ghrelin level (Keith et al., 2006).

Lastly, pollution could also affect body weight through behavioral responses. Many studies find that people are likely to stay indoors in response to elevated air pollution levels (Neidell, 2009), reduce physical activities, and increase sedentary behaviors such as sitting, reclining, and lying (Jerrett et al., 2010; McConnell et al., 2014; Li et al., 2015; An et al., 2018b). These behaviors may reduce the net calories expended and increase body weight and obesity risk (WHO, 2018a). Air pollution could also lead to a direct increase in calories consumed. For example, Chen et al. (2018) find that air pollution is likely to induce a variety of mental illness, such as depression and anxiety, which could release the hormone cortisol and increase appetite for energy-intensive foods, insulin resistance, and fat accumulation (Björntorp, 1997). Building on these observational studies, the goal of this paper is to formally test the proposition that air pollution is causally related to evaluated body weight and overweight and obesity risks.

3 Empirical Strategy

Our goal is to estimate the causal effect of air pollution on various indicators of body weight. The primary empirical challenge is the omitted-variable bias. As a byproduct of economic activity, air pollution is typically correlated with many economic confounders, such as income and food prices. These confounders are also important determinants of body weight, while their impacts could be either positive or negative. For example, additional income could either increase or decrease body weight. If both high-caloric food/sedentary pursuits and good health/appearance are normal goods, additional income will increase their consumption. If more high-caloric food/sedentary pursuits are consumed than good health/appearance, additional income could increase body weight, and vice versa. Indeed, researchers have documented an inverted U-shaped relationship between income and weight (Philipson and Posner, 2003; Lakdawalla et al., 2005).

Because of the ambiguous effect of economic confounders on body weight as well as the correlation between air pollution and those economic confounders, the bias direction of air pollution on body weight is a priori unknown. To help identify the causal effect, we rely on an instrumental variables approach. In particular, we use thermal inversions, which is a meteorological phenomenon, to instrument for air pollution.

Under normal conditions, the temperature in the upper atmospheric layer is lower than that of the surface layer. Therefore, air pollutants can be transmitted from the ground to the upper layer and further be spread out. Under certain circumstances (see Arceo et al. (2016)), the temperature in the upper layer is higher than that of the ground layer, thereby forming a thermal inversion. Air pollutants are thus trapped near the ground leading to high air pollution concentrations.

Given that thermal inversions are a meteorological phenomenon, their formation is typically independent of economic activity. Figure 2 illustrates this point by plotting the average annual cumulative thermal inversions over 1989–2011[5]. Unlike $PM_{2.5}$, which has a clear time trend, the frequencies of thermal inversions are relatively random. To ensure that our instrument meets the exclusion restriction criteria, we control for flexible weather variables so that thermal inversions affect body weight only through air pollution. Thermal inversions have been used as IV for air pollution in several studies, including Hicks et al. (2015), Arceo et al., (2016), Chen et al. (2017), Fu et al., (2017), Chen et al. (2018), and Jans et al. (2018).

We propose the following 2SLS model to estimate the causal effect of air pollution on body weight:

$$Y_{it} = \beta_0 + \beta_1 P_{it} + f(W_{it}) + \gamma_i + \sigma_t + \varepsilon_{it} \quad (1)$$

$$P_{it} = \alpha_0 + \alpha_1 I_{it} + f(W_{it}) + \gamma_i + \sigma_t + u_{it} \quad (2).$$

In the model, Y_{it} denotes the body weight measures, including BMI, and indicators for overweight and obesity for individual i at date t. We use P_{it} to denote the average concentration of $PM_{2.5}$. Note that we do not have a priori specified the exposure window, as this remains generally unknown from the previous literature. In other words, we do not know how long air pollution will affect body weight. As a baseline, we choose an exposure window of 12 months. For example, if an individual's BMI was measured on June 15, 2000 in county c, we use the average concentration of $PM_{2.5}$ from July 1999 to June 2000 for that county. Since our pollution data are only available at monthly level, we cannot construct an exposure window based on specific dates, (i.e., June 16, 1999 to June 15, 2000). We conduct

[5] For each dot, we sum all thermal inversions (determined with each six-hour period) in a given county and year, and then average over all counties for each year.

two robustness checks on the exposure window. First, we vary the exposure window from one month to 18 months. Second, we exclude the current month when we construct the 12-month exposure window[6].

We instrument P_{it} using the number of thermal inversions, denoted by I_{it}, in the same exposure window. We use $f(W_{it})$ to denote weather variables in flexible specifications in the same exposure window. Specifically, we use the number of days within each 5 °C bin and the quadratics of average relative humidity, sunshine duration, wind speed, and pressure, and cumulative precipitation. We include individual fixed effects, γ_i, to control for any time-invariant and individual-specific characteristics that may be related to body weight and exposure to air pollution, such as gender, baseline metabolism, and geographic locations. We include year-by-month fixed effects (denoted by σ_t), to control for nation-wide seasonality in air pollution, economic conditions, and overall health.

We use two-way clustering (Cameron et al., 2011) at the individual and county-year-month levels. This controls for the autocorrelation in the measurements for the same individual across different survey years as well as the autocorrelation within each county-year-month cell. Our results are robust to alternative clustering methods, which we discussed in the Results section.

In summary, our identification relies on comparing BMI of the same individual in a more inversion-intensive and thus more polluted year versus a less

[6] For example, if an individual's BMI was measured on June 15, 2000, our baseline $PM_{2.5}$ measure uses the average from July 1999 to June 2000, while our alternative measure uses the average from June 1999 to May 2000.

inversion-intensive and polluted year, after we adjust the year-specific seasonality and weather shocks.

4 Data

4.1 BMI and obesity

We obtain BMI data from the CHNS, which is one of the longest and most comprehensive longitudinal health surveys in China and is still ongoing. The CHNS is jointly conducted by the University of North Carolina at Chapel Hill and the Chinese Center for Disease Control and Prevention. The survey covered 15,000–19,000 individuals in 4400–7200 households from nine provinces[7] (two-digit code)[8] over the period of 1989–2011[9]. The sample was selected using a multistage random cluster sampling method. Specifically, for each province, two cities (four-digit code) and four counties (six-digit code) were randomly selected. The survey then randomly selected urban districts (six-digit code) for cities and villages and towns for counties. These areas were defined as communities. Finally, households were randomly selected from these communities. This dataset has been used in several previous studies (e.g., Wang, 2011 and Wang, 2013).

[7] The nine provinces are Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou.

[8] China has three administrative levels, namely, provinces/municipal cities (two-digit code), prefectures/cities (four-digit code), and counties/districts (six-digit code). See http://www.stats.gov.cn/tjsj/tjbz/tjyqhdmhcxhfdm/.

[9] The years are 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011.

The CHNS provides detailed information on health and nutrition as well as socioeconomic and demographic characteristics for both rural and urban households in China. One key advantage of the CHNS is that the body weight and height are measured by medical staff instead of being self-reported by the interviewee. This is important because individuals tend to underreport their weight, especially for heavier individuals (Cawley et al., 2015). We calculate BMI using the body weight measured in kilograms (kg) divided by the square of the body height measured in square meters (m^2). The unit of BMI is thus kg/m^2. Note that this formula only applies to adults aged 18 or above, and thus our main sample only includes adults. We focus on children aged 2–17 in Section 5.7. We define a person is overweight if BMI>=25, and obese if BMI>=30 (WHO, 2018a)[10].

4.2 Air pollution

Our data on air pollution are from the satellite-based Aerosol Optical Depth (AOD) retrievals. In particular, we obtain the AOD data from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) from the NASA of the U.S. The data are available at 50*60-km grid level for each month since 1980. We calculate the concentration of $PM_{2.5}$ following the formula provided by Buchard et al. (2016). We then aggregate from grid to county for each month[11] and

[10] Overweight sometimes is defined between 25 and 30. In this case, obesity is excluded from the overweight category. Therefore, our measure on overweight includes both overweight and obesity.

[11] The aggregation is conducted as follows. First, we downscale the original 50*60-km grid by five times using the bilinear method (Hijmans et al., 2015). This is because some counties are smaller than the 50*60-km grid. We then take the average for all downscaled grids within each county.

further average to the 12-month exposure window. This dataset has been used in previous studies (Chen et al., 2017; Fu et al., 2017), and validated with ground-based pollution data in China (Chen et al., 2017). We do not use ground-based pollution data mainly because they are only available after 2000 and covered only a few cities.

4.3 Thermal inversions

We also obtain the thermal inversions data from MERRA-2. The data report air temperature for each 50*60-km grid for 42 atmospheric layers, ranging from 110 meters to 36,000 meters. The data are available at six-hour periods from 1980 onwards. We aggregate all data from grid to county using the same method used for the air pollution data. We determine the existence of a thermal inversion if the temperature in the second layer (320 meters) is higher than that of the first layer (110 meters) for each six-hour period, and then aggregate the number of inversions to the 12-month exposure window.

4.4 Weather

The weather data are obtained from the National Meteorological Information Center, which releases daily weather variables, including temperature, precipitation, relative humidity, sunshine duration, wind speed, and pressure for more than 800 weather stations in China. We use the inverse-distance weighting (IDW) method to convert weather data from station to county level and choose a radius of 200 km. To account for the possible non-linear effects of temperature, we calculate the number of days within each 5 °C bin in the 12-month exposure window. For other weather variables, we use average relative humidity, sunshine duration, wind speed and pressure, and cumulative precipitation in the same period. We also include the quadratic of each weather variables except for temperature bins to account for the non-linear effects.

4.5 Summary statistics

Our final sample has 13,226 adult individuals from 71 counties/districts across eight provinces over 1989–2011[12]. Figure 1A in the Online Appendix plots the number of interviewees in each survey year. There were 3,569 interviewees in 1989, and the number of interviewees increased to 7,729 to 1991 and was relatively stable afterwards. Thus, our sample is an unbalanced panel. Figure A2 in the Online Appendix shows the frequency of interviews per interviewee. A total of 3,586 (27%) and 2,127 (16%) were interviewed twice and thrice, respectively. Only 757 individuals (6%) are present throughout the entire sample period.

One concern is that pollution may induce people to move (Chen et al., 2017) and thus bias our estimates. Note that the individual fixed effects should absorb all initial sorting into difference places, including sorting based on differential pollution levels. Therefore, only individuals moving during our sample period can potentially bias the estimates. The survey asked the moving status of each individual for the household. In our final sample, 99.71% of individuals remained in the same county.

[12] The county identifiers are not available for Heilongjiang Province.

Given this low rate of mobility, our results are robust if we only use the individuals who remained in the same county.

An important feature of the CHNS design is that interviews are only conducted from July to December, with 90% of the total interviews conducted between September and November (Figure A3 in the Online Appendix). Thermal inversions also have a strong seasonality mainly because of climatic related factors. Figure A4 in the Online Appendix plots the average of the monthly cumulative thermal inversions across months[13]. It is clear that most inversions occurred in the non-summer months. This differential seasonality in the natural occurrence of thermal inversions and timing of the CHNS interviews dictate that we define exposure windows that are long enough to stretch across thermal inversions seasons. Our baseline focuses on a 12-month exposure window where CHNS interviews are linked to air pollution and thermal inversions recorded over the preceding 12 months.

This seasonality should not bias our baseline estimates for two reasons. First, the interview time changes minimally across years because the majority are concentrated in the Fall. Thus, for our baseline exposure window, i.e., 12 months, we mainly use year-to-year variations (e.g., October 1999 to September 2000 versus October 2003 to September 2004), instead of season-to-season variations across years (e.g., October 1999-September 2000 versus June 2003-May 2004). Second, we include year-by-month fixed effects, which control for the unobserved shocks specific to particular year-month combinations.

[13] For each dot, we sum all thermal inversions (determined with each six-hour period) in a given county and month, and then average over all counties in the same month.

Table 1 reports the summary statistics. We have three measures of body mass: BMI, and the indicators for overweight and obesity (reported as percentage points in the table). We also report the average weight and height. In our sample, the average BMI is 22.62 with a standard deviation of 3.30. The average BMI is 23.76 in 2011, which is the most recent period. Figure 3 plots the histogram of BMI and shows that most observations are centered between 18 and 25. There are some extreme values, with the minimum of 4.83 and maximum of 63.78. Our results are robust if we drop the top and bottom 0.5% of the data.

The average overweight and obesity rates are 21.47% and 2.52% during our sample period, with 32.84% and 4.90% respectively in 2011. The average body weight is 58.03 kg, and average height is 159.92 cm. Females account for 52% of the observations and have slightly higher BMI and overweight and obesity rates than males. The same pattern has been found in the U.S. (National Center for Health Statistics, 2014) and the world (WHO, 2018a).

The average concentrations of $PM_{2.5}$ are 63 $\mu g/m^3$, which are six times higher than the WHO standard of ten $\mu g/m^3$ (WHO, 2006). The concentration varies from a minimum of 23.75 to a maximum 141.32, with a standard deviation of 26.19. The average annual cumulative inversion times are 269.50. Since the occurrence is determined at each six-hour period, the probability of having an inversion in any given year is 269.50/(4*365)=18.46%.

5 Results

5.1 Effect of thermal inversions on air pollution

Table 2 reports the estimated effect of thermal inversions on $PM_{2.5}$ concentrations. In column (1), we include individual fixed effects and year fixed effects. In column (2), we replace year fixed effects with year-by-month fixed effects, to control for year-specific seasonality. In the last column, we further add detailed weather controls.

Overall, we find a strong first-stage relationship. The estimated coefficients are stable across specification and statistically significant at the 1% level. Moreover, the KP *F*-statistic in the preferred specification in column (3), which includes weather controls, is well above the Stock-Yogo critical value of 16.38 (Stock and Yogo, 2005). The magnitude is also significant and suggests that one additional thermal inversion (0.37% of the mean) in the past 12 months increases $PM_{2.5}$ concentrations in the same period by 0.03 $\mu g/m^3$ (0.05% of the mean), corresponding to an elasticity of 0.14.

5.2 2SLS estimates of the effect of air pollution on body mass

Table 3 reports the main 2SLS estimates of the impact of air pollution on various indicators of body mass. The dependent variables are BMI in columns (1) and (2), indicators for overweight in columns (3) and (4) and obesity in columns (5) and (6). Panel A reports the 2SLS estimates while Panel B reports the fixed-effect estimates when air pollution is not instrumented. All columns include individual fixed effects and weather controls. Columns (1), (3), and (5) include year fixed effects while columns (2), (4), and (6) include year-by-month fixed effects.

Several important results emerge from this table. First, we find a statistically significant and economically large effect of $PM_{2.5}$ on BMI. Our preferred specification, column (2), shows that a 1 $\mu g/m^3$ (1.59%) increase in average $PM_{2.5}$ concentrations in the past 12 months increases BMI by 0.0691 units (0.31%). This corresponds to an elasticity between $PM_{2.5}$ and BMI of 0.19. We can also convert the magnitude using standard deviations. The point estimates indicate that a one standard deviation increase in $PM_{2.5}$ concentrations increases the BMI by 0.55 standard deviations.

Second, air pollution increases the probability of being overweight. Column (4) reports that a 1 $\mu g/m^3$ increase in average $PM_{2.5}$ concentrations in the past 12 months increases the probability of being overweight by 0.89 percentage points, or 4.15 percent of the mean. In other words, a one standard deviation increase in $PM_{2.5}$ in the past 12 months increases the probability of being overweight by 0.57 standard deviations.

Third, the effect of $PM_{2.5}$ on obesity rates is smaller and statistically weaker. This may be because only few individuals are obese: in our sample, the obesity rate is only 2.52 percent.

Fourth, considering the standard errors, the 2SLS point estimates are similar between the model with year fixed effects and year-by-month fixed effects, thereby suggesting that residual seasonality in air pollution and determinants of body weight does not confound our estimation strategy. Recall that most interviews were conducted in the Fall, and thus we mainly use year-to-year variation, instead of season-to-season variation across years.

Lastly, the fixed-effects estimates in Panel B are remarkably smaller in magnitude compared to the 2SLS estimates in Panel A. This underscores the importance of instrumenting for air pollution as confounders and measurement error may have biased the OLS estimates downwards.

5.3 Robustness checks

We report the results of various robustness checks in Tables 4a and 4b. Column (1) is the baseline model, in which we use year-by-month fixed effects to control for nation-wide year-month shocks. In column (2), we replace the year-by-month fixed effects with date fixed effects as a more flexible control for unobserved China-wide temporal shocks. The corresponding point estimates and standard errors are relatively larger.

In column (3), we replace year-by-month fixed effects with province-by-year-by-month fixed effects, which controls for the province and year-specific monthly unobserved shocks. This leads to a larger coefficient and standard errors as this specification is more demanding of the data. Since the first-stage diagnostic KP F-statistic is only 7.75, we use year-by-month fixed effects as the baseline time fixed effects for the rest of the analysis.

Our baseline model includes weather variables in flexible specifications. This is to satisfy the exclusion restriction and ensure that air pollution is the only channel through which thermal inversions affect body weight. In column (4), we exclude weather controls and the magnitude and statistical significance of the estimated coefficients changes little.

Our baseline exposure window is 12 months, and we include the current month of the interview. For example, if an individual was interviewed on June 15 2000, we construct the exposure window from July 1999 to June 2000. In column (5), we drop the current month, and construct the exposure window from June 1999 to May 2000. This change in the exposure window does not lead to a meaningful change in the estimates.

Column (6) of Table 4B tests the robustness of our IV construction. In our baseline model, we define thermal inversions using the temperature difference between the first (110 meters) and the second layers (320 layers). In column (6), we replace the second layer with the third layer (540 meters). The results are very similar.

We then test the robustness of excluding extreme values of BMI from the sample in column (7). Specifically, we winsorize the top and bottom 0.5% observations, and the results are essentially unchanged.

The definitions for overweight (BMI>=25) and obesity (BMI>=30) are taken from the WHO, which are derived mainly from Western populations. Zhou (2002) proposed that the BMI cutoff of 24 for overweight and 28 for obesity is more appropriate for the Chinese populations. Using these new cutoffs, the average overweight and obesity rates in our sample are 30.01% and 6.37% respectively, larger than the WHO cutoff (21.47% and 2.52% respectively). Column (8) reports the estimates using the new standards. The effect on overweight is very similar to the baseline model. However, we find a much larger (around 2.5 times) and more precisely estimated effect on obesity compared to the baseline model.

Our BMI measure is derived from body weight and height. In columns (9) and (10), we estimate the effect of air pollution on body weight and height separately. As expected, we find a statistically significant effect of $PM_{2.5}$ on body weight. Specifically, a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations increases the body weight by 0.1858 kg, or 0.32% (mean=58.03 kg). On the contrary, the effect on body height is statistically insignificant and close to zero. This provides a placebo test for confounders. Since our sample only includes adults (age>=18), their body heights should not change in response to air pollution.

Finally, in column (11), we use the 12 months after the interview as the exposure window to conduct a falsification test. As expected, the estimates are small and statistically insignificant, suggesting that unobserved secular trends do not confound our results.

Table A1 in the Online Appendix reports the estimates under different assumptions on the clustering of the standard errors. Column (1) is the baseline model, with two-way clustering and clustered standard errors at the individual and county-year-month levels. In column (2), we keep the individual clustering and change the county-year-month to county-year clustering, which allows for autocorrelation in the errors within a county-year cell. In column (3), we further aggregate the clustering level from county-year to county. This controls for any autocorrelation within each county across years. In column (4), we use two-way clustering at the county and year level. In the last two columns, we employ the one-way clustering and cluster at county-year and county level, respectively. Our results are generally significant at the 5% level for most specifications.

5.4 Alternative exposure windows

In this section, we explore the effects of different exposure windows. Our baseline model uses a 12-month exposure window. In Figure 4, we vary the exposure window from the past month to the past 18 months. The dependent variables are BMI in Panel A, and the overweight and obesity indicators in Panels B and C. The point estimates are denoted by dots and the 95% confidence intervals are denoted by whiskers.

The estimated effects of air pollution for the one- to three-month exposure windows are close to zero and statistically insignificant at the 5% level. The 95% confidence intervals become very large when the exposure windows extend from four to nine months. This is mainly because the first-stage relationship between thermal inversions and air pollution is weak due to differential seasonality in interview times and natural occurrence of thermal inversions (Figures A3 and A4 in the Online Appendix).

When we further extend the exposure windows from 10 to 18 months, the confidence intervals shrink again, and the estimated coefficients are statistically significant for the exposure window of 11–13 months at the 5% level. It appears from this analysis that exposure to air pollution over the course of several months is necessary to cause an increase in body weight. The relatively precise "zero" estimates in the first three months lead us to conclude cautiously that the pollution effect is not contemporaneous, or at least not within the three months.

5.5 Heterogeneity analysis

Table 5 reports estimates for various sub-groups. We start with gender in columns (1) and (2). In China, females have higher BMI and overweight and obesity rates than males. The estimated impact of $PM_{2.5}$ on the three body weight measures are larger for females. However, the gender differences appear insignificant given the size of the standard errors.

Columns (3) and (4) reports estimated impacts by age group. The elderly (aged above 60) accounts for 20% of the sample, and they tend to have higher BMI and overweight and obesity rates than adults aged below 60. However, the estimated effects of $PM_{2.5}$ are smaller in magnitude and statistically insignificant for the elderly.

Next, we explore the heterogeneity by education levels. Since the survey covered a significant amount of rural residents, and the survey started in 1989, when China was in the early stage of development, the average education level in the sample is low. Table A3 in the Online Appendix reports the sample size and the average BMI and overweight and obesity rates by seven educational groups. Nearly 30% of individuals have not received any formal education. Around 20% and 30% of the individuals graduated from primary school and junior high school, respectively. Less than 20% of the population graduated from high school or above.

Researchers typically find that people with higher education tend to be in better health, and obesity is no exception (Grossman, 2006; Cawley, 2015). However, the case appears to be different for China. Overall, BMI as well as the overweight and obesity rates are larger in the highest educational group. This may be because those highly educated individuals have higher income, and the income-obesity gradient in China is still in the increasing part of the inverted U-shaped relationship.

Because of the small size of the seven educational groups, we merge them into two groups: lower education with no or only primary school education, and higher education with senior high school education or above. Columns (5) and (6) report the 2SLS estimates of air pollution on body weight for each educational group separately. The impacts are larger for the highly educated group, especially for the impact on overweight. This heterogeneity could be caused by differences in behavioral responses to air pollution across educational groups. For example, the better educated group may spend more time exercising in normal conditions. If this is the case, a positive pollution shock may reduce exercise time and increase body weight because the better educated may have more information on the harmful effects of air pollution.

The last two columns explore the heterogeneity by urban and rural residencies. Rural individuals account for 55% of observations and have lower BMI and overweight and obesity rates than urban individuals. The estimated impact of $PM_{2.5}$ on body weight, however, do not differ much between urban and rural residents.

5.6 Suggestive tests about the mechanisms

Section 2 discussed several mechanisms through which air pollution may affect body weight. In this section, we use limited survey data to provide simple tests of possible behavioral channels, including changes in physical and sedentary activity, bed time, and food intake. The main issue with the survey is that it only asked the respondents to report their behaviors within a very short time window, such as the past three days or one week. As shown in Figure 4, the effect of air pollution on body weight is detectable only with an exposure windows of at least 9–10 months. Therefore, we failed to detect any meaningful short-run behavior responses. Nevertheless, we report the results in Table 6 as suggestive evidence.

We start with types of activities. The survey asked how many minutes a respondent spent on physical and sedentary activities[14] in a typical week and how many hours sleeping or lying in bed in a typical day. Because our pollution data are at the monthly level, we use the $PM_{2.5}$ in the month of the interview. Overall, we do not find any significant effects.

We then focus on food intake. The CHNS recorded detailed information on total calories consumed and by different categories during the past three days. The

[14] Physical activity includes martial arts such as Kung Fu, gymnastics, dancing, acrobatics, and sports, while sedentary activities include watching TV, playing computer games, reading, writing, and drawing. Note that around 94% and 6.6% of observations have zero values for these two questions.

dependent variable in column (4) is the total calories consumed. Although the sign is positive, i.e., high pollution increases calories intake, it is estimated very imprecisely. Through columns (5) to (7), the dependent variables are nutrition intake for each category, including carbohydrate, fat, and protein. We cautiously interpret these findings as suggestive evidence that air pollution increases fat and protein intake but reduces carbohydrate intake[15].

5.7 Impact on air pollution on children body weight

We now focus on children and teens aged 2–17. Unlike overweight and obesity in adults which are defined by widely accepted cutoffs of BMI, childhood obesity is usually determined by comparing to peers of the same age and sex. We follow the standards of the Centers for Disease Control and Prevention (CDC) of the U.S., and define a child as overweight (obese) if the BMI is at or above the 85th (95th) percentile for children and teens of the same age and sex[16].

There is also a high prevalence of childhood obesity. In 2016, the prevalence of obesity among children and teens aged 5–19 was 18%, while this number was only 4% in 1975 (WHO, 2018a). Table A4 in the Online Appendix reports the summary statistics for body mass of children aged 2–17. The prevalence of overweight and

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[15] In the above estimates, we use the $PM_{2.5}$ concentrations in the month of the interview. We also used the average $PM_{2.5}$ concentrations in the past 12 months, but did not find any significant effects. We also used the reduced-form estimate, i.e., thermal inversions on each behavior responses, and used the corresponding exposure window, i.e., past seven days for physical and sedentary activity, one day for bed time, and past three days for nutrition intake. Again, we failed to find any meaningful effects.

[16] See details here https://www.cdc.gov/obesity/childhood/defining.html.

obesity are 10.15% and 4.15% during our sample period, and boys have higher overweight and obesity rates.

Figure 5 plots the 2SLS estimates of the effect of $PM_{2.5}$ on childhood overweight (Panel A) and obesity (Panel B) for exposure windows from the month of the interview up to the prior 18 months. Unlike for the results for adults where we find a significant effect for exposure windows of past 11–13 months, the effects for children are significant for shorter exposure windows (e.g., 4–6 months). These findings may suggest that the behaviors and physiology of children and teens respond to air pollution faster. The estimate for exposure window of the past five months suggests that a 1 $\mu g/m^3$ increase in average $PM_{2.5}$ concentrations increase the prevalence of overweight and obesity by 2.09 and 1.62 percentage points respectively, which is higher than the effect for adults.

6 Discussion

This paper documents a statistically significant positive effect of air pollution on BMI, overweight, and obesity rates. In this section, we compare our estimates with those from two strands of the literature: those estimating the causes of obesity and those estimating the economic cost of air pollution. In the last two subsections, we discuss the policy implications and research caveats as well as future research directions.

6.1 Comparison with the literature on estimating the causes of obesity

In the past several decades, the prevalence of overweight and obesity has increased significantly in the U.S. and other developed countries (National Center for Health Statistics, 2014; OECD, 2014). Therefore, economists have devoted considerable attention to understand the economic causes of obesity (see Cawley (2015) for a literature review).

First, we compare our estimates with Currie et al. (2010), who estimate the effect of fast food restaurants on obesity rates in the U.S. They find that the presence of a fast food restaurant within 0.1 miles of a school increases the obesity rates by 5.2 percent for the ninth graders. This effect is similar to the increase of average $PM_{2.5}$ concentrations by 1 μg/m^3, as we find that a 1 μg/m^3 increases the obesity rate by 0.19 percentage points, or 7.54 percent.

Second, we compare our estimates with Brunello et al. (2013), who investigate the effect of education on obesity. They find an insignificant impact of schooling on obesity for males. However, the effect is significantly positive for females. Specifically, a 1 additional year of schooling reduces the prevalence of obesity by 14.83 percent for women. As we do not find statistically significant gender differences in response to air pollution, we use our estimate for the whole sample. Therefore, we can conclude that a 1 additional year of schooling has a similar effect with a decrease of $PM_{2.5}$ concentrations by around 2 (14.83/7.54) μg/m^3.

Lastly, we focus on peer and neighborhood effects. Using the Moving to Opportunity program as an experiment, Kling et al. (2007) find that moving to a low-poverty neighborhood reduces the probability of obesity by 4.8 percentage points relative to the control group. This reduction is equivalent to reducing $PM_{2.5}$ concentrations by 25.26 μg/m^3. In summary, we find that the impact of air pollution on obesity in China is meaningful and comparable to other economic causes.

6.2 Comparison with the literature on estimating the economic cost of air pollution

Overweightness and obesity can lead to a variety of chronic diseases such as diabetes, cardiovascular and kidney diseases, and some cancers, and therefore contribute considerably to social medical costs. To shed light on the economic cost of air pollution on overweight and obesity, we perform a back-of-the-envelope calculation using the estimated response to a 1 μg/m^3 increase in $PM_{2.5}$ concentrations, multiplying by the per-capita health expenditure attributable to overweight and obesity.

Qin and Pan (2015) estimate that overweight and obese people account for 5.29% of total personal health expenditure in China during 2000–2009. In 2016, the per-capita health expenditure in China was CNY 3,784 (China Statistical Yearbook, 2017), and thus the overweight/obesity-related health expenditure per capita was CNY 200. Since we find that a 1 μg/m^3 increase in average $PM_{2.5}$ concentrations increases the prevalence of overweight (including obesity) by 0.89 percentage points (column (4) of Table 3), we can conclude that this increase in $PM_{2.5}$ concentrations induces a per-capita health cost of CNY 1.78 (200*0.0089) on average, and a total health cost of CNY 2.05 billion (1.78*1.15 billion adults), or USD 0.31 billion on overweight and obesity.

We can also compare our estimates with previous studies that estimate the effect of $PM_{2.5}$ on other economic variables. Deryugina et al. (2016) find that a 1 $\mu g/m^3$ decrease in $PM_{2.5}$ brings an annual benefit of USD 4.11 billion in terms of avoided mortality in the U.S., which is 13 times larger than our estimate. Fu et al. (2017) and Chang et al. (2019) find that a 1 $\mu g/m^3$ decrease in $PM_{2.5}$ increases labor productivity in China by USD 2.99 billion and in the U.S. by USD 6.99 annually, which is 10 and 23 times larger than our estimate respectively.

To sum up, our study suggests that the cost of air pollution on overweight and obesity are non-trivial. Although the magnitude is smaller than previous studies focused on other economic variables, it is in the same order of scale. We may underestimate the costs for two reasons. First, we only focus on medical costs, but researchers have found that obesity has wide impacts on economic outcomes, including wages (Cawley, 2004) and employment (Rooth, 2009). Second, the estimated percent of medical cost attributable to overweight and obesity in Qin and Pan (2015) was calculated during the period of 2000–2009. Since the prevalence of overweight and obesity is expected to increase in China, the related medical cost will also be likely to increase in the future.

6.3 Policy implications

Many developing countries have remarkably poor air quality, which is often considered as one of the first-order obstacles to economic development. In China, Premier Li Keqiang has declared “The War against Air Pollution” and many acts and regulations have been promulgated to reduce air pollution.

On the other hand, the Chinese government has begun to realize the increasing prevalence of overweight and obesity and the associated economic burden in China, and therefore have implemented several policies on obesity prevention and control. For example, in 2003, the Bureau of Disease Control issued the Guidelines for Prevention and Control of Overweight and Obesity of Chinese Adults. In 2013, the nutrient information should be included on labels. Taken together, our study shows that reducing air pollution could be an important and effective strategy to reduce overweight and obesity in China, and could have large benefits in terms of avoided health expenditure on overweight and obesity.

6.4 Caveats and future research direction

At least two caveats exist in our study. First, due to the research design, i.e., using thermal inversions as the IV for $PM_{2.5}$, we cannot identify the effect of $PM_{2.5}$ per se, because air pollutants are highly correlated with one another, and thermal inversions could also affect other air pollutants, such as PM_{10}, CO, and O_3 (Arceo et al., 2016). Therefore, it is better to interpret our estimates as the effect of air pollution, instead of $PM_{2.5}$ per se, on body weight.

Second, although we believe our causal estimates of air pollution on body weight are convincing, the mechanism tests are not determined precisely in the data and can only be interpreted as suggestive. This is mainly because the data on several behavioral responses such as exercising, dieting, and sleeping were only collected over short periods. Therefore, we cannot isolate the behavioral channel from the physiological channel. Future research should utilize better data on behavioral responses.

Although our focus is on China, our methods are general and could be applied to other countries. In fact, it is not clear whether air pollution will affect body weight in a different context, e.g., for developed countries. Even so, it remains unknown about the magnitude, which may differ because exposure to air pollution, and the behavioral and biological responses are different across countries. We leave this for future research.

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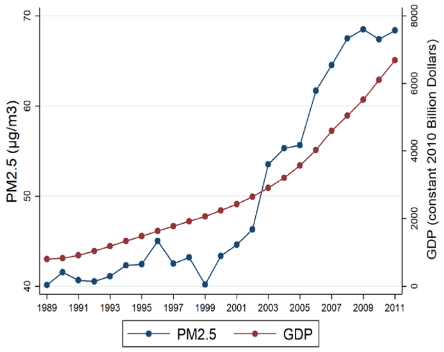
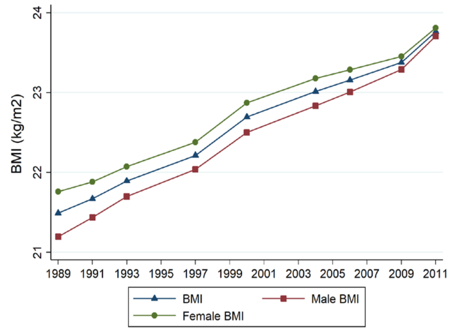
Figure 1. Trends of $PM_{2.5}$ concentrations, GDP, and Body Weight in China during 1989-2011

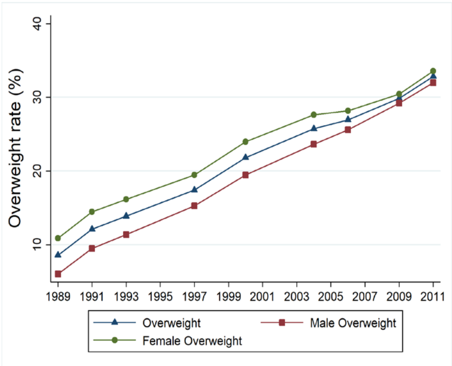
Panel A



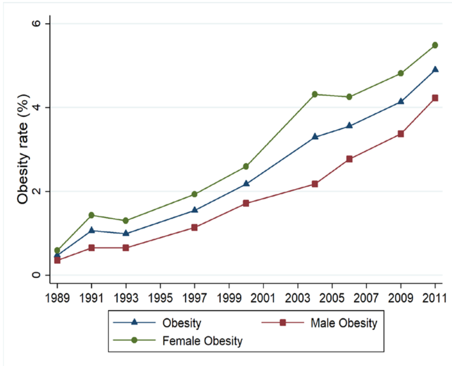
Panel B



Panel C

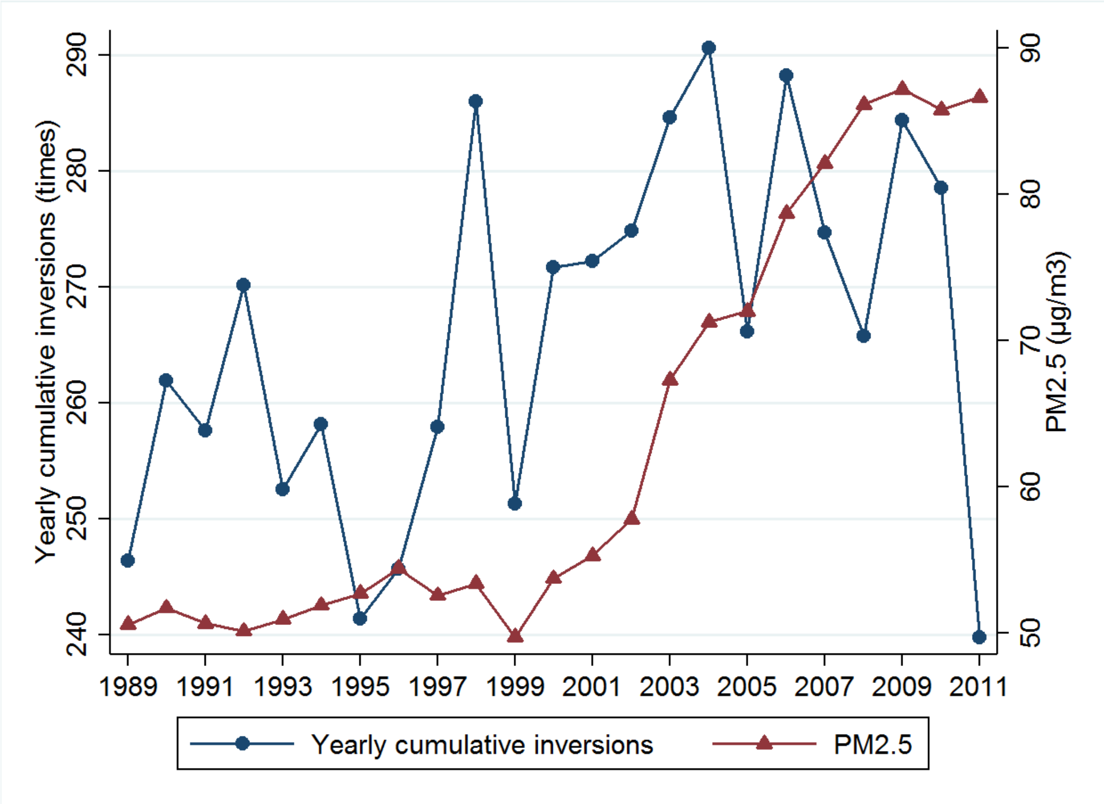


Panel D



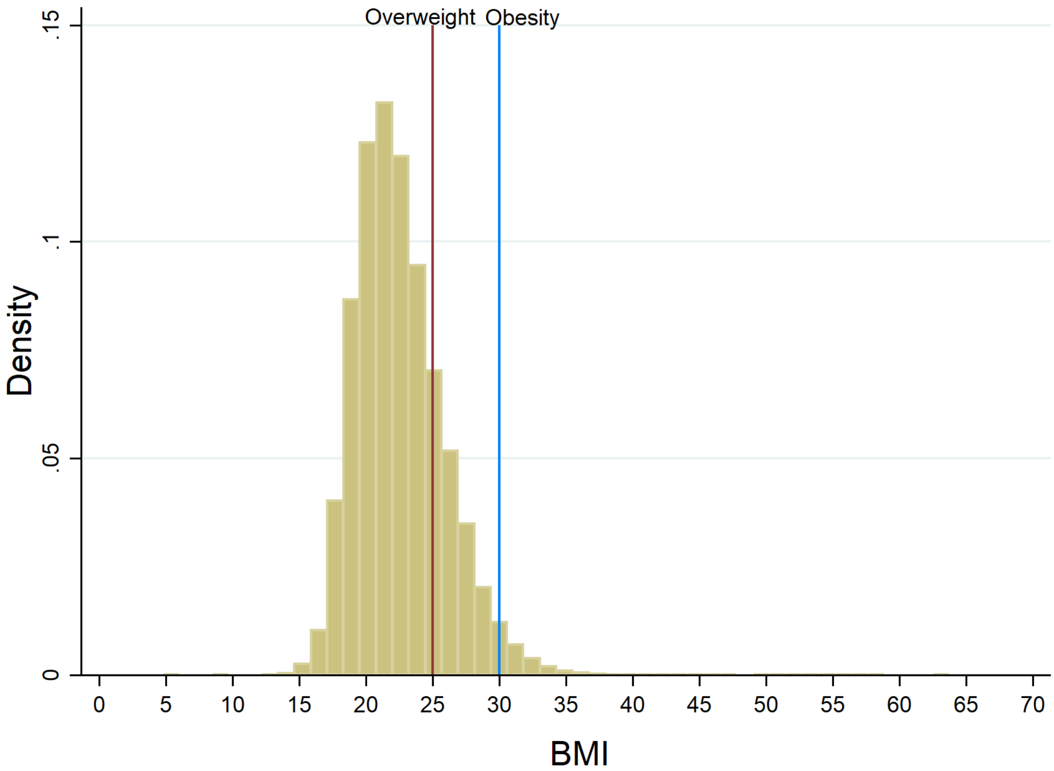
Notes: This figure shows the annual average of $PM_{2.5}$ concentrations and GDP (Panel A), average BMI (Panel B), the prevalence of overweight (BMI>=25, Panel C), and obesity (BMI>=30, Panel D) for adults (age>=18) in China during 1989-2011. The data on GDP are from the National Bureau of Statistics of China and are deflated using the 2010 price. The data on $PM_{2.5}$ are from the NASA. The data on BMI, overweight, and obesity are from the China Health and Nutrition Survey. $PM_{2.5}$ is the average for the whole country, and BMI, overweight, and obesity are the average for the 71 counties/districts across eight provinces in the sample.

Figure 2. Trends of Thermal Inversions and $PM_{2.5}$ during 1989-2011



Notes: This figure plots the annual average $PM_{2.5}$ concentrations and annual cumulative thermal inversions for the 71 sample counties and districts in China over 1989-2011.

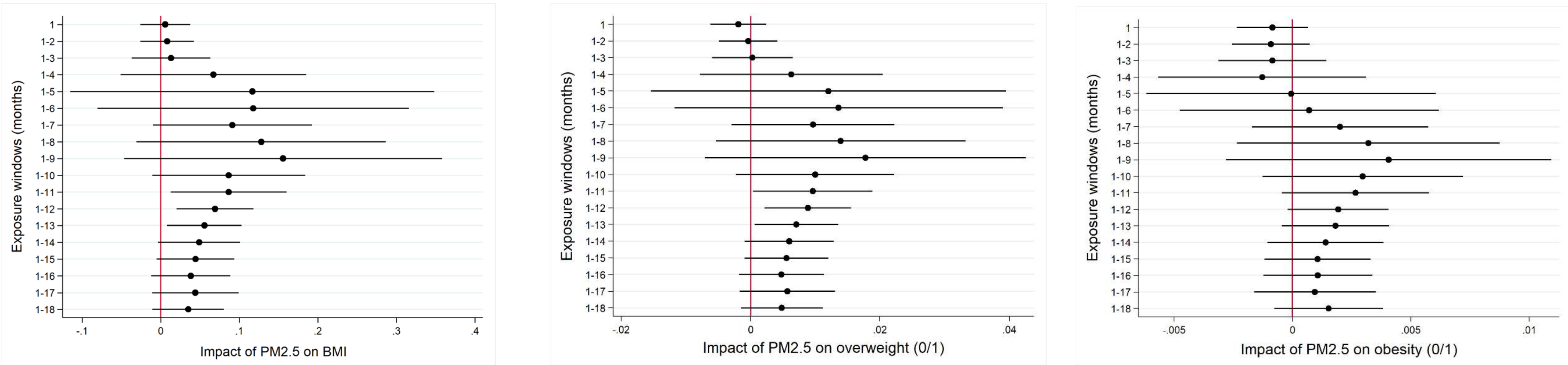
Figure 3. Distribution of Body Mass Index (BMI) in China, 1989-2011



Notes: This figure plots the histogram of BMI. The vertical red line indicates the cutoff of 25, which is used to define overweight. The vertical blue line indicates the cutoff of 30, which is used to define obesity.

Figure 4. Impacts of $PM_{2.5}$ on Body Weight

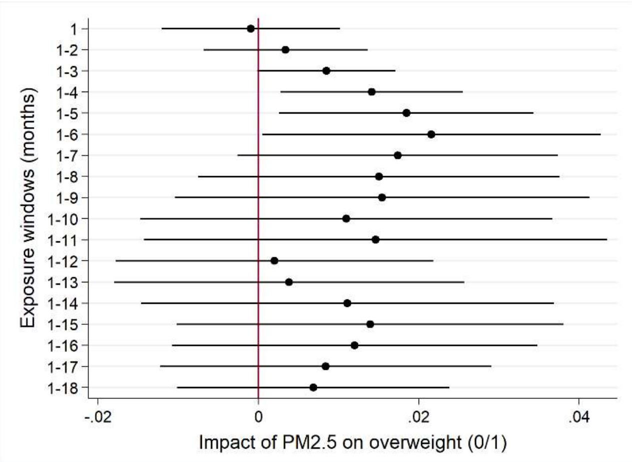
Panel A Panel B Panel C



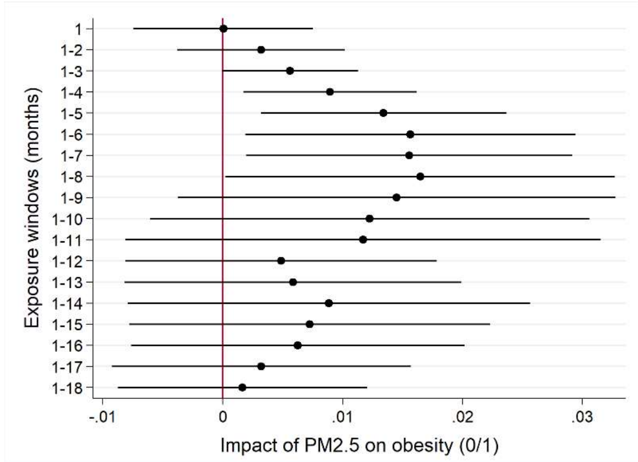
Notes: This figure depicts the impacts of $PM_{2.5}$ on the BMI (Panel A), overweight (Panel B), and obesity (Panel C). The model is estimated using Equation (1). $PM_{2.5}$ is calculated using average concentrations from the month of the interview to the past 18 months. The circle denotes the point estimate, and the whisker denotes the 95% confidence intervals. Standard errors are clustered at individual and county-year-month level (two-way clustering).

Figure 5. Impact of $PM_{2.5}$ on Body Weight (Children Aged 2-17)

Panel A



Panel B



Notes: This figure depicts the impacts of $PM_{2.5}$ on overweight (Panel A) and obesity (Panel B) for children aged 2-17. The model is estimated using Equation (1). $PM_{2.5}$ is calculated using average concentrations from the month of the interview to the past 18 months. The circle denotes the point estimate, and the whisker denotes the 95% confidence intervals. Standard errors are clustered at individual and county-year-month level (two-way clustering).

Table 1. Summary Statistics

Variable	Description	N	Mean	SD	Min	Max
Body mass measure						
BMI	weight/height^2 (kg/m^2)	60,056	22.62	3.30	4.83	63.78
Percent Overweight	BMI>=25	60,056	21.47	41.06	0	100
Percent Obese	BMI>=30	60,056	2.52	15.69	0	100
Weight	kg	60,056	58.03	10.56	15.00	162.70
Height	cm	60,056	159.92	8.42	105.00	188.00
Male						
BMI	weight/height^2 (kg/m^2)	28,548	22.45	3.16	4.83	57.01
Percent Overweight	BMI>=25	28,548	19.53	39.64	0	100
Percent Obese	BMI>=30	28,548	1.93	13.76	0	100
Weight	kg	28,548	61.83	10.48	15.00	162.70
Height	cm	28,548	165.73	6.48	105.00	188.00
Female						
BMI	weight/height^2 (kg/m^2)	31,508	22.78	3.41	9.03	63.78
Percent Overweight	BMI>=25	31,508	23.23	42.23	0	100
Percent Obese	BMI>=30	31,508	3.06	17.23	0	100
Weight	kg	31,508	54.6	9.40	24.00	156.80
Height	cm	31,508	154.66	6.23	120.60	179.00
Air pollution						
$PM_{2.5}$	μg/m^3	60,056	63.00	26.19	23.75	141.32
Thermal inversions						
inversions	Times in 12 months (defined over 6-hour intervals)	60,056	269.50	116.87	71	578

Notes: N=60,056. Unit of observation is individual-year. The survey covered 13,226 adult individuals (age>=18) from 71 counties across eight provinces during 1989-2011 in China. The BMI is calculated using the weight (kg) divided by squared height (m^2). Overweight is a dummy variable which equals one if BMI is above or equals 25. Obesity is a dummy variable which equals one if BMI is above or equals 30. $PM_{2.5}$ is average concentration at monthly level. Thermal inversion is determined within each six-hour period, and then aggregated to the 12 months.

Table 2. First-stage Estimation: Effects of Thermal Inversions on $PM_{2.5}$

	$PM_{2.5}$		
	(1)	(2)	(3)
Thermal inversions	0.0253***	0.0251***	0.0283***
	(0.0064)	(0.0064)	(0.0062)
Individual FE	Yes	Yes	Yes
Year FE	Yes	No	No
Year-by-month FE	No	Yes	Yes
Weather controls	No	No	Yes
KP *F*-statistics	15.66	15.31	20.92

Notes: N=60,056. The dependent variable is average monthly $PM_{2.5}$ concentrations over the 12-month exposure window. Thermal inversions are aggregated from each 6-hour to 12 months. Weather controls include 5°C temperature bins, second-order polynomials in average relative humidity, wind speed, sunshine duration, and cumulative precipitation. Standard errors listed in parentheses are clustered at individual and county-year-month level (two-way clustering). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3. Second-stage Estimation: Effects of Air Pollution on Body Mass

	BMI		Overweight (0/1)		Obesity (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS						
$PM_{2.5}$	0.0473**	0.0691***	0.0069**	0.0089***	0.0016	0.0019*
	(0.0226)	(0.0249)	(0.0030)	(0.0034)	(0.0010)	(0.0011)
KP *F*-statistics	21.69	20.92	21.69	20.92	21.69	20.92
Panel B: FE						
$PM_{2.5}$	0.0001	-0.0006	-0.0003	-0.0004	-0.0003	-0.0003
	(0.0039)	(0.0037)	(0.0005)	(0.0005)	(0.0002)	(0.0002)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Year-by-month FE	No	Yes	No	Yes	No	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: N=60,056. The dependent variables are: BMI in columns (1)-(2), an overweight indicator in columns (3)-(4), and an obesity indicator in columns (5)-(6). Panel A reports 2SLS estimate, in which we use number of thermal inversions as an instrument for $PM_{2.5}$. Panel B reports the fixed-effect estimates which air pollution is not instrumented. Weather controls include 5 °C temperature bins, second-order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors in parentheses are clustered at individual and county-year-month level (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Table 4A. Robustness Checks

	Baseline	Date FE	Province-by year-by-month FE	No Weather Controls	Exclude current month
	(1)	(2)	(3)	(4)	(5)
Panel A: BMI					
PM $_{2.5}$	0.0691***	0.1082**	0.1363*	0.0851***	0.0769**
	(0.0249)	(0.0439)	(0.0775)	(0.0302)	(0.0312)
Panel B: Overweight (0/1)					
PM $_{2.5}$	0.0089***	0.0146**	0.0186*	0.0119***	0.0104**
	(0.0034)	(0.0062)	(0.0109)	(0.0043)	(0.0044)
Panel C: Obesity (0/1)					
PM $_{2.5}$	0.0019*	0.0031*	0.0027	0.0023*	0.0025*
	(0.0011)	(0.0019)	(0.0030)	(0.0012)	(0.0014)
KP *F*-statistics	20.92	12.8	7.75	15.31	13.33
Observations	60,056	60,056	60,056	60,056	60,056

Notes: The dependent variables are: BMI in Panel A, an overweight indicator in Panel B, and an obesity indicator in Panel C. Column (1) is the baseline model and uses year-by-month fixed effect. Column (2) replaces year-by-month fixed effects with date fixed effects. Column (3) replaces year-by-month fixed effects with province-by-year-by-month fixed effects. Column (4) excludes weather controls. Column (5) excludes the current month to construct the exposure window. *** p<0.01, ** p<0.05, * p<0.1.

Table 4B. Robustness Checks

	Alternative layers for IV	Winsorize	Cutoff change	Body Weight	Body Height	Lead 12 Months
	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: BMI						
$PM_{2.5}$	0.0655***	0.0723***	-	0.1858***	0.0005	-0.0057
	(0.0235)	(0.0248)	-	(0.0649)	(0.0318)	(0.0266)
Panel B: Overweight (0/1)						
$PM_{2.5}$	0.0096***	0.0090***	0.0085**	-	-	-0.0012
	(0.0031)	(0.0034)	(0.0035)	-	-	(0.0036)
Panel C: Obesity (0/1)						
$PM_{2.5}$	0.0013	0.0022**	0.0050**	-	-	-0.0017
	(0.0010)	(0.0011)	(0.0021)	-	-	(0.0013)
KP *F*-statistics	25.51	21.04	20.92	20.92	20.92	10.3
Observations	60,056	59,395	60,056	60,056	60,056	52,577

Notes: Column (6) changes the instrumental variables by coding thermal inversions with the temperature difference between the first (110 meters) and the third layers (540 meters). Column (7) drops the top and bottom 0.5% observations of the BMI. Column (8) reports the estimates with new BMI cutoff of 24 for overweight and 28 for obesity. Columns (9)-(10) estimate the effect of air pollution on body weight and height separately. Column (12) uses the lead 12 months as the exposure window. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effect of Air Pollution on Body Mass : By Gender, Age, Educational Attainment, and Rural/Urban Residency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Age<60	Age≥60	Low education	High education	Urban	Rural
Panel A: BMI								
PM $_{2.5}$	0.0744***	0.0656**	0.0614**	0.0511	0.0647**	0.0822**	0.0534**	0.0581**
	(0.0281)	(0.0284)	(0.0239)	(0.0372)	(0.0251)	(0.0371)	(0.0271)	(0.0249)
Mean of Dep.Var	22.45	22.78	22.59	22.68	22.53	22.69	23.01	22.30
S.D. of Dep. Var.	3.16	3.41	3.1592	3.7403	3.35	3.24	3.41	3.17
Panel B: Overweight (0/1)								
PM $_{2.5}$	0.0114**	0.0067*	0.0098***	0.0017	0.0051	0.0171**	0.0080*	0.0063*
	(0.0044)	(0.0037)	(0.0036)	(0.0046)	(0.0032)	(0.0069)	(0.0042)	(0.0034)
Mean of Dep.Var	0.20	0.23	0.21	0.24	0.21	0.22	0.26	0.18
S.D. of Dep. Var.	0.40	0.42	0.40	0.43	0.41	0.41	0.44	0.38
Panel C: Obesity (0/1)								
PM $_{2.5}$	0.0024*	0.0015	0.0022*	0.0001	0.0016	0.0032	0.0015	0.0020*
	(0.0013)	(0.0014)	(0.0012)	(0.0024)	(0.0011)	(0.0022)	(0.0016)	(0.0010)
Mean of Dep.Var	0.02	0.03	0.02	0.04	0.03	0.02	0.03	0.02
S.D. of Dep. Var.	0.14	0.17	0.15	0.19	0.16	0.15	0.17	0.14
Observations	28,548	31,508	46,900	12,090	29,239	28,516	27,077	32,979
KP *F-statistics*	19.89	21.32	22.33	25.23	29.58	12.09	24.26	17.78

Notes: The dependent variables are: BMI in Panel A, an indicator for overweight in Panel B, and an indicator for obesity in Panel C. Regression models are estimated separately for each subsample. Low educated refers to those who received primary-school education or below, and high educated refers to those who received senior high-school education or above. Weather controls include 5 °C temperature bins, second-order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors in parentheses are clustered at individual and county-year-month (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

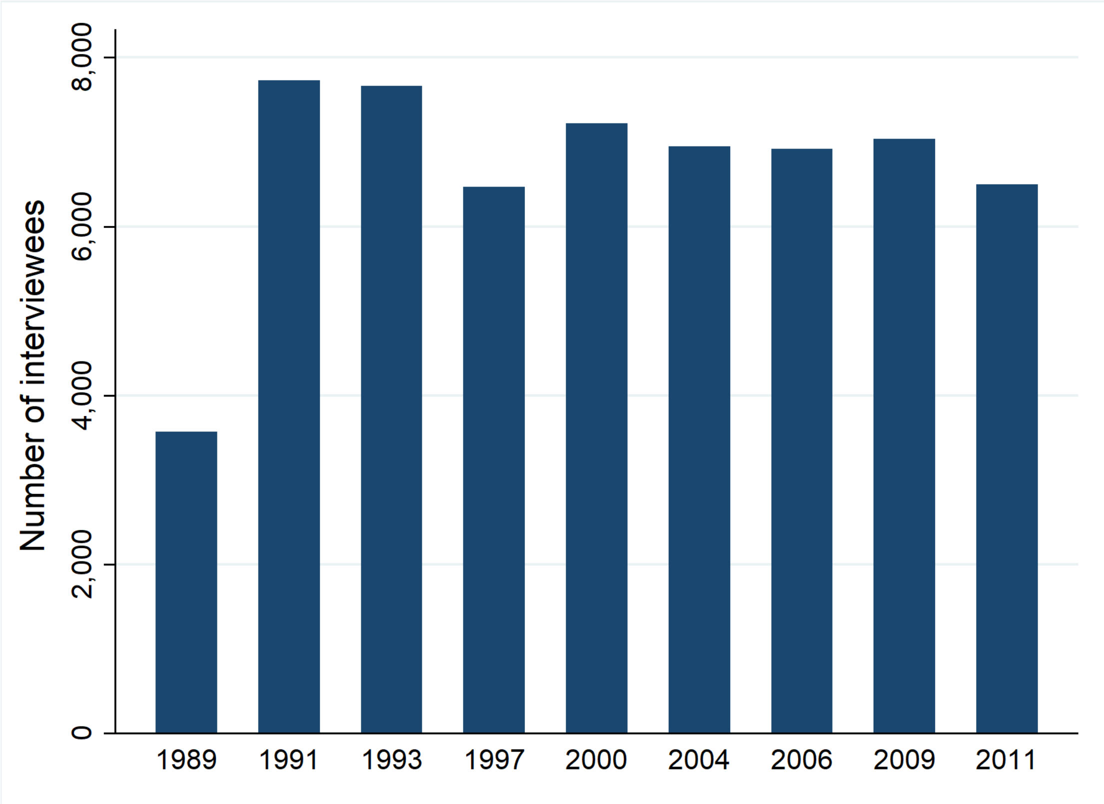
Table 6. Air Pollution Effects on Activities and Nutrition Intake

	Activities			Nutrition Intake			
	Physical activity (typical week)	Sedentary activity (typical week)	Bed time (typical day)	Energy (past 3 days)	Carbo (past 3 days)	Fat (past 3 days)	Protein (past 3 days)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	mins	mins	hours	kcal	g	g	g
$PM_{2.5}$ Recent 1 mo.	0.2579	-0.6880	-0.0031	2.7920	-0.0198	0.2133	0.1246
	(0.2537)	(1.9032)	(0.0114)	(9.9628)	(1.6880)	(0.5161)	(0.3680)
Mean of Dep.Var	8.94	287.83	8.03	2309.14	345.68	69.53	69.50
S.D. of Dep. Var.	46.32	220.79	1.29	758.09	132.88	46.39	25.69
Observations	36,693	24,437	25,460	54,929	54,929	54,929	54,929
% of zeros	94.04	6.59	0.05	0	0	0	0
# of individual	9,801	8,119	8,351	12,633	12,633	12,633	12,633
KP *F*-statistics	16.00	15.13	14.59	12.07	12.07	12.07	12.07

Notes: The dependent variables are physical activities (minutes) in column (1) and sedentary activities (minutes) in column (2) in a typical week, total hours at bed in a typical day in column (3), energy intake (kcal) in column (4), carbohydrate (g) intake in column (5), fat (g) intake in column (6), and protein (g) intake in column (7) for past three days. Physical activity includes martial arts such as Kung Fu, gymnastics/dancing/acrobatics, running/swimming, soccer/basketball/tennis, badminton/volleyball, and others such as table tennis and Tai Chi. Sedentary activities include watching TV, watching videotapes/VCD/DVD, playing video games, surfing the internet, online chatting, playing computer games, and reading/writing/drawing. The exposure window is one month. Weather controls include 5 °C temperature bins, second-order polynomials in average relative humidity, wind speed, and sunshine duration, and cumulative precipitation. Standard errors listed in parentheses are clustered at individual and county-year-month level (two-way clustering). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

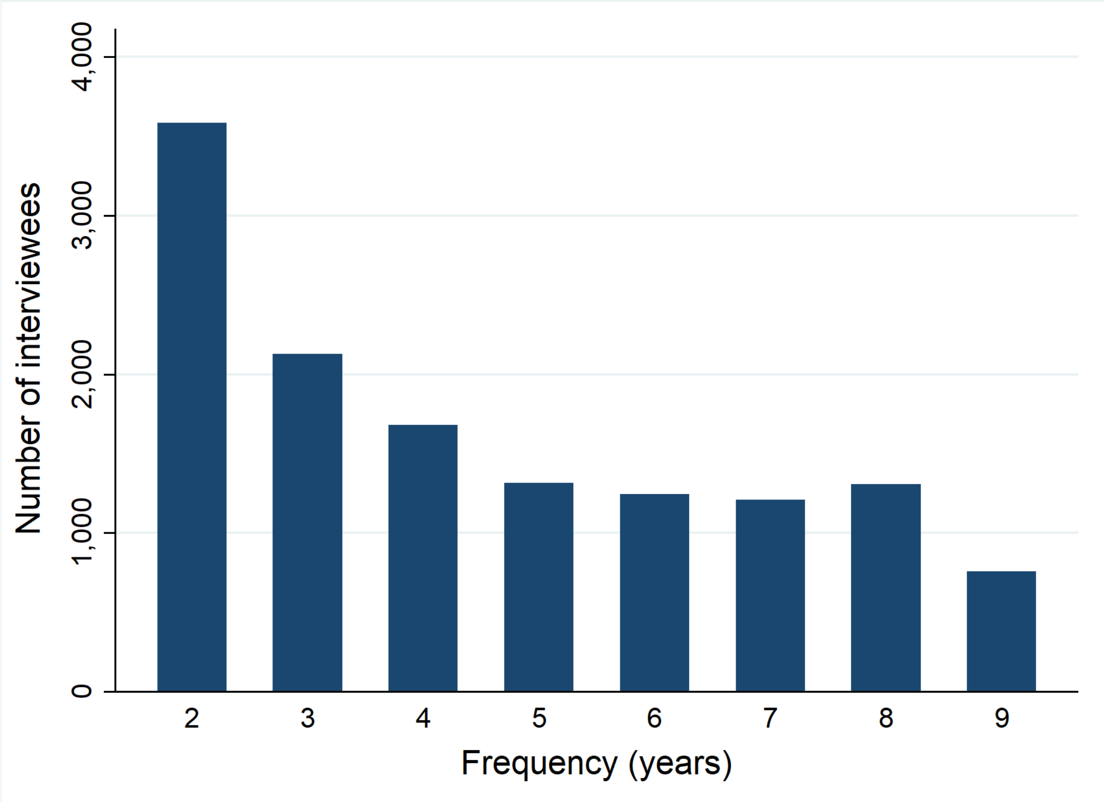
Online Appendix

Figure A1. Number of Interviewees across Years



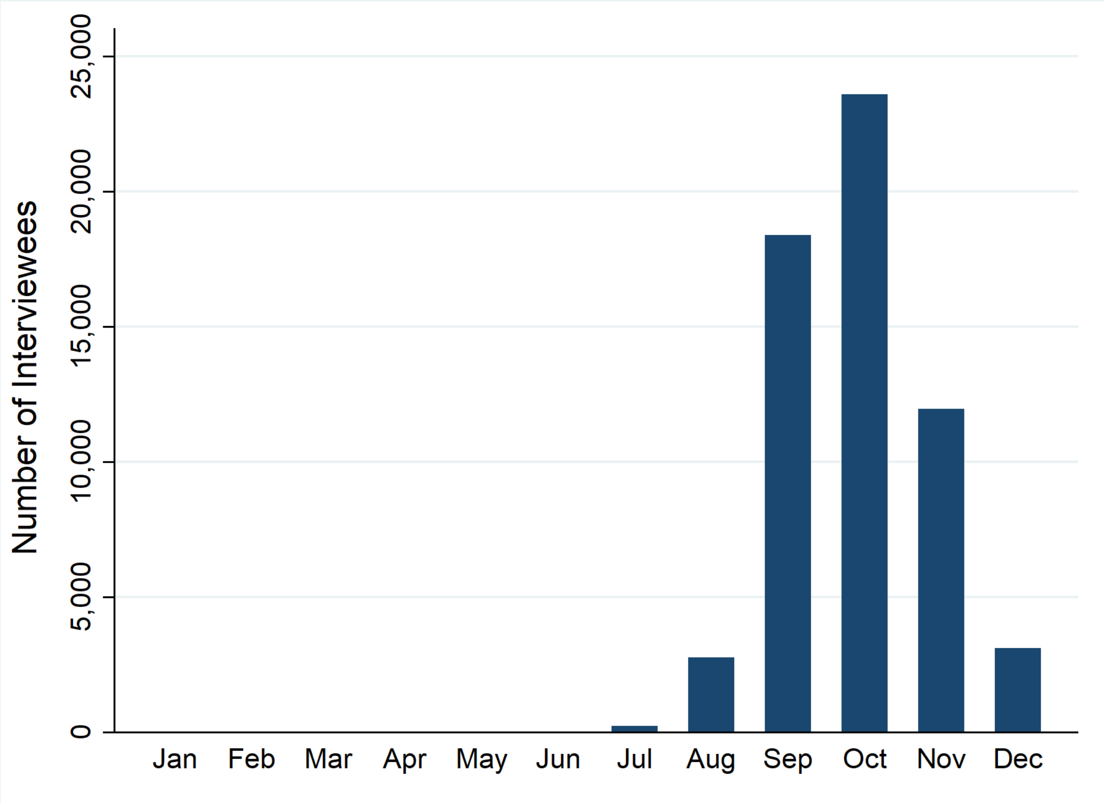
Notes: This figure plots the number of interviewees in each survey year (1989-2011).

Figure A2. Frequency of Interviewees



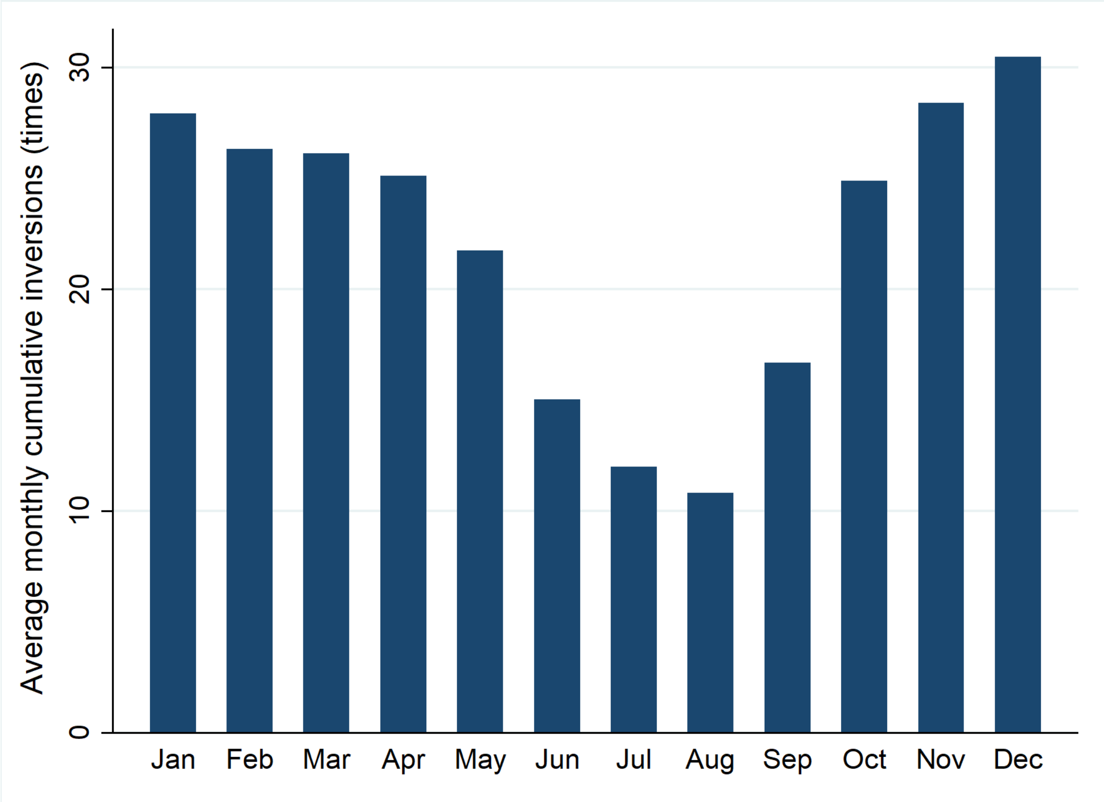
Notes: This figure plots the frequency in years for number of interviewees.

Figure A3. Number of Interviewees across Months



Notes: This figure plots the aggregate number of interviewees across months.

Figure A4. Average of Thermal Inversions across Months



Notes: This figure plots the average number of monthly cumulative thermal inversions for all 71 counties across months.

Table A1. Robustness Checks on Clustering of Standard Errors

	Two-way: Individual and county-year-month	Two-way: Individual and county-year	Two-way: Individual and county	Two-way: County and year	One-way: Count-year	One-way: County
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: BMI						
$PM_{2.5}$	0.0691***	0.0691***	0.0691**	0.0691*	0.0691**	0.0691**
	(0.0249)	(0.0254)	(0.0329)	(0.0319)	(0.0276)	(0.0329)
Panel B: Overweight (0/1)						
$PM_{2.5}$	0.0089***	0.0089**	0.0089**	0.0089**	0.0089**	0.0089**
	(0.0034)	(0.0035)	(0.0040)	(0.0036)	(0.0037)	(0.0040)
Panel C: Obesity (0/1)						
$PM_{2.5}$	0.0019*	0.0019*	0.0019*	0.0019*	0.0019*	0.0019*
	(0.0011)	(0.0011)	(0.0011)	(0.0009)	(0.0011)	(0.0011)
KP F-statistics	20.92	18.50	9.400	7.896	14.53	9.400

Notes: N=60,056. The dependent variables are: BMI in Panel A, an indicator variable for overweight in Panel B, and an indicator variable for obesity in Panel C. Column (1) is the baseline model and uses the two-way clustering: individual and county-year-month. Column (2) uses two-way clustering: individual and county-year. Column (3) uses two-way clustering: individual and county. Column (4) uses two-way clustering: individual and year. Column (5) uses one-way clustering: county-year. Column (6) uses one-way clustering: county. All models include individual fixed effects, year-by-month fixed effects, and weather controls. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. First-stage Results for Alternative Exposure Windows

	Current month	Average 2 months	Average 3 months	Average 4 months	Average 5 months	Average 6 months
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal inversions	0.1093***	0.0687***	0.0377***	0.0168*	0.0100	0.0107
	(0.0344)	(0.0229)	(0.0140)	(0.0098)	(0.0085)	(0.0078)
KP *F*-statistics	10.12	8.973	7.214	2.951	1.393	1.881
	Average 7 months	Average 8 months	Average 9 months	Average 10 months	Average 11 months	Average 12 months
	(7)	(8)	(9)	(10)	(11)	(12)
Thermal inversions	0.0180**	0.0143*	0.0126*	0.0176**	0.0212***	0.0283***
	(0.0077)	(0.0075)	(0.0075)	(0.0070)	(0.0063)	(0.0062)
KP *F*-statistics	5.475	3.622	2.854	6.276	11.46	20.92
	Average 13 months	Average 14 months	Average 15 months	Average 16 months	Average 17 months	Average 18 months
	(13)	(14)	(15)	(16)	(17)	(18)
Thermal inversions	0.0248***	0.0204***	0.0201***	0.0190***	0.0173***	0.0197***
	(0.0056)	(0.0050)	(0.0047)	(0.0046)	(0.0047)	(0.0045)
KP *F*-statistics	19.49	16.50	18.30	17.03	13.53	19.09

Notes: N=60,056. The dependent variable is $PM_{2.5}$. $PM_{2.5}$ is calculated using average concentrations from one to past 18 months. Thermal inversions are aggregated from one to past 18 months. Standard errors listed in parentheses are clustered at individual and county-year-month level (two-way clustering). *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Mean of Body Mass by Educational Groups

Level	Category	BMI	Percent Overweight	Percent Obese	N
0	No Schooling	22.47	20.70%	2.66%	17,242
1	Primary school	22.64	21.12%	2.75%	12,831
2	Junior high School	22.61	21.03%	2.33%	17,998
3	Senior high School	22.78	22.51%	2.17%	7,176
4	Technical college	22.94	26.07%	2.82%	2,447
5	College/university	23.10	26.05%	2.50%	1,762
6	Graduate school	23.24	27.03%	2.70%	37

Notes: This table presents the mean of body mass by educational groups.

Table A4. Summary Statistics（Children aged 2-17）

Variable	Description	N	Mean	SD	Min	Max
Body mass measure						
Overweight	>=85th percentile	15,619	10.15%	0.30	0	1
Obesity	>=95th percentile	15,619	4.15%	0.20	0	1
Weight	kg	15,619	30.00	13.97	7.6	93
Height	cm	15,619	129.63	24.08	68.5	189
Male						
Overweight	>=85th percentile	8,286	11.32%	0.32	0	1
Obesity	>=95th percentile	8,286	5.01%	0.22	0	1
Weight	kg	8,286	30.61	14.59	8	93
Height	cm	8,286	130.46	24.78	70	189
Female						
Overweight	>=85th percentile	7,333	8.84%	0.28	0	1
Obesity	>=95th percentile	7,333	3.18%	0.18	0	1
Weight	kg	7,333	29.312	13.20	7.6	89.8
Height	cm	7,333	128.69	23.24	68.5	180.5

Notes: This table reports the summary statistics for children and teens aged 2-17.