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The effect of air pollution on body weight and obesity: Evidence from China

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ABSTRACT

We provide the first study estimating the causal effect of air pollution on body weight and obesity. Using the China Health and Nutrition Survey, which contains detailed longitudinal health and socioeconomic information for 13,741 adult individuals over 1989–2015, we find significant positive effects of air pollution, instrumented by thermal inversions, on body weight. Specifically, a 1 μg/m^3 (1.54%) increase in average $PM_{2.5}$ concentrations in the past 12 months increases body mass index by 0.27%, and also increases overweight and obesity rates by 0.82 and 0.27 percentage points, respectively. We also find evidence that these impacts can be explained in part by a variety of behavioral channels, including less physical activity, less walking to work or school, less sleep, and more fat intake.

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 Risk Factor Collaboration, 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).

In response to this epidemic, numerous economics studies have sought to understand the complex and varied causes of obesity.[1] This paper provides the first attempt at estimating the causal link between ambient air pollution, and particularly, fine particulate matter ($PM_{2.5}$)[2] and obesity. At present, over 90% of the global population lives in places with poor air quality. Understanding the link between air pollution and obesity is thus crucial for policy makers.

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 797 billion in 1989 to USD 8.89 trillion in 2015. Meanwhile, the national average concentration of $PM_{2.5}$ increased from 40.1 to 66.9 μg/m^3 (Panel A of Fig. 1). In the same period, the prevalence of overweight and obesity has also increased rapidly. The average BMI increased by 12.7%, while overweight and obesity rates increased from 8.29% to 38.48% and from 0.46% to 5.83%, respectively (Panels B–D of Fig. 1). In 2014, China ranked first in obese men (16.3% of global obesity) and women (12.4% of global obesity) (NCD Risk Factor Collaboration, 2016).

Air pollution can affect body weight through biological channels (e.g., slowing down the metabolism) and behavioral channels (e.g., reducing exercise and increasing calorie intake).[3] Although previous health science studies have suggested multiple potential pathways between air pollution exposure and body weight, identifying the causal effect is challenging primarily because of the potential for omitted-variable bias. For example, air pollution is a byproduct of economic activity, and thus potentially correlated with economic confounders, such as income and food prices, which are also important determinants of obesity (Cawley, 2015).

In order to identify the causal effect of air pollution on body weight,

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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] See detailed discussion in Section 2.

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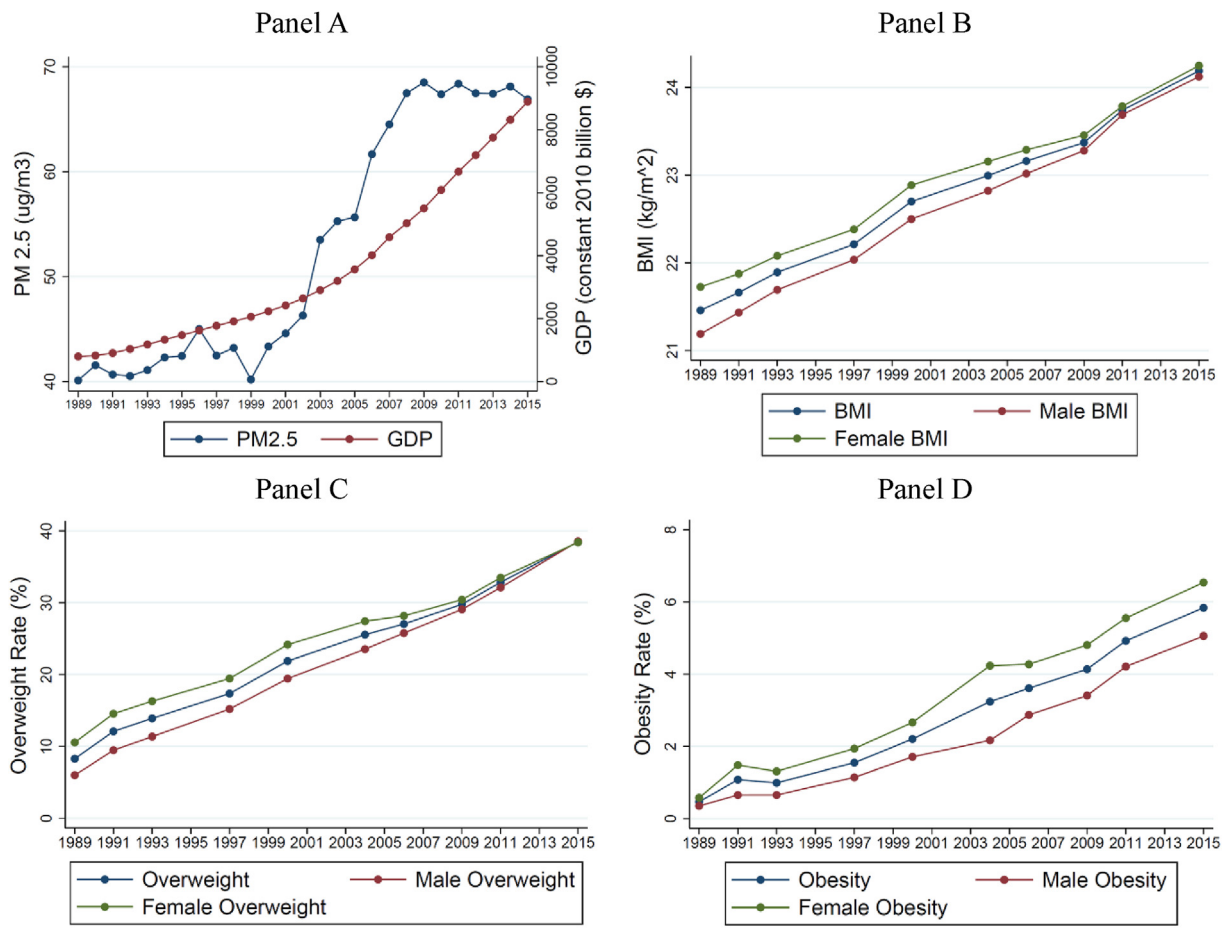


Notes: This figure shows the annual average of PM2.5 concentrations and GDP (Panel A), average BMI (Panel B), the prevalence of overweight (BMI>=25, Panel C), and obesity (BMI>=30, Panel D) for adults (age>=18) in China during 1989-2015. The data on GDP are from the National Bureau of Statistics of China and are deflated using the 2010 constant dollars. 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.

Fig. 1. Trends of $PM_{2.5}$, GDP, and Body Weight in China during 1989–2015.

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 inversions is a complex meteorological phenomenon and is typically independent of economic activities, as we demonstrate below. Importantly, we utilize the longitudinal structure of our health survey data and include individual fixed effects in our models for body weight indicators and air pollution. Therefore, identification is driven by fluctuations in air pollution instrumented by variation in arguably exogenous thermal inversions across different years for the same individual. In addition, we flexibly control for weather and include year-by-month fixed effects to control for seasonality in environmental and economic conditions.

We use data on body weight and height 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 13,741 adult individuals (aged 18 or older) from eight provinces in China over the period of 1989–2015. Notably, the data on body weight and height, which we use to define BMI, are recorded by survey enumerators instead of being self-reported, which should greatly improve their accuracy and mitigate concerns about measurement error bias. We then match the CHNS data with satellite-based pollution and thermal inversions data by county of residence and month of the interview for each interviewee.

Using a two-stage least squares (2SLS) estimator, we find a positive and statistically significantly effect of $PM_{2.5}$ on body weight. Specifically, a 1 $\mu g/m^3$ (1.54%) increase in average $PM_{2.5}$ concentrations in the past 12 months increases BMI by 0.27%, and increases the overweight and obesity rates by 0.82 and 0.27 percentage points, respectively. The dynamics of exposure to air pollution matter: we do not detect significant short-run effects coming from exposure to air pollution in the first three months following an interview.

We then study the effect of pollution on behavioral responses including physical and sedentary activities, sleeping, transportation mode, and calorie intake. We find that air pollution reduces physical

activity, the probability of walking to work or school, sleeping time, and increases fat intake. This suggests that behavioral channels play an important role in the pollution-obesity relationship.

This paper contributes to two strands of the literature. First, a large body of literature estimates the cost of air pollution on a variety of economic outcomes, including mortality and morbidity (Chay and Greenstone, 2003; Schlenker and Reed Walker, 2015; Deschenes et al., 2017; Deryugina et al., 2019), labor productivity (Graff Zivin and Neidell, 2012), labor supply (Hanna and Oliva, 2015), and test scores (Ebenstein et al., 2016). We identify a new chronic morbidity cost of air pollution, and find that a 1 $\mu g/m^3$ increase in average $PM_{2.5}$ concentrations induces a total of CNY 1.89 billion (USD 0.27 billion) health expenditure on overweight and obesity.

Second, an emerging 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, can also play an important role in causing 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).

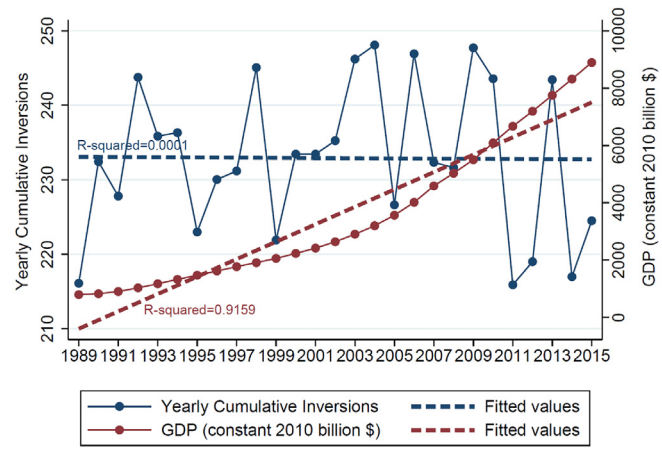
Third, air pollution could affect body weight through sleep disorders. Researchers have found that air pollution causes sleeplessness (Heyes and Zhu, 2019).

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).

A few studies in the health science literature estimate the correlation between air pollution and obesity using regression models. For example, Li et al. (2016) focus on 2372 participants from the Framingham Offspring and Third Generation cohorts in the U.S., and find that participants who lived near a major roadway (where the air is more polluted) have higher BMI and obesity rates. Similarly, Li et al. (2015) focus on 24,845 Chinese adults, and find a positive correlation between air pollution and obesity.

Overall, these studies do not have proper identification strategies and are lacking of tests of the mechanisms linking air pollution and body weight. The goal of this paper is to formally test if air pollution is causally related to elevated body weight and obesity risks, and test a few possible behavioral mechanisms.



Notes: This figure shows the national trends of thermal inversion and GDP between 1989 and 2015. GDP is deflated to 2010 constant dollars.

Fig. 2. Trends of Thermal Inversions and GDP in China during 1989–2015.

3. Empirical strategy

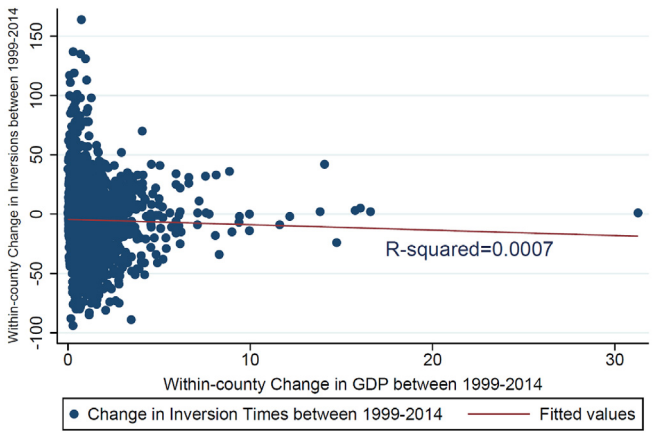
The primary empirical challenge for identifying the causal effect of air pollution on body weight is the potential for omitted-variable bias. As a byproduct of economic activity, air pollution is typically correlated with many economic confounders, such as income and food prices. These confounders can also be important determinants of body weight, and their independent effects could be either positive or negative. In particular, additional income could either increase or decrease body weight. For example, if both high-caloric food and health investments are normal goods, additional income will increase their consumption, which can lead to weight increases or decreases. Indeed, researchers have documented an inverted U-shaped relationship between income and weight (Philipson and Posner, 1999; 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, a meteorological phenomenon, as an instrumental variable 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 transported from the surface 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. In that case, air pollutants are trapped near the ground leading to high air pollution concentrations.

Given that thermal inversions are a high atmosphere meteorological phenomenon, their formation can be presumed independent of economic activity. Fig. 2 supports this hypothesis by plotting annual GDP and the average annual cumulative thermal inversions for all counties in China over 1989–2015.[4] GDP has a clear positive trend with an R-square of 0.9159. On the other hand, the number of thermal inversions per year highly fluctuates and does not have a clear time trend. The fitted line (shown with a dashed line) is almost horizontal and the R-square is only 0.0001.

[4] For each dot, we sum all thermal inversions (determined with each 6-h period) in a given county and year, and then average over all counties for each year.



Notes: This figure plots the within-county change in GDP and thermal inversions in China between 1999 and 2014. GDP is deflated to 1999 constant billion dollars.

Fig. 3. Within-county Change in GDP and Thermal Inversions in China between 1999–2014.

In Fig. 3, we show further evidence that thermal inversions are not correlated with economic activity. We plot the change in GDP (X-axis) and the change inversions (Y-axis) for each county in China between 1999 and 2014.[5] It is evident that all counties experienced positive changes in GDP. On the other hand, about half of counties experience positive changes in thermal inversions and half experience negative changes. In addition, the counties having the highest increase in GDP do not necessarily have the highest increase or decrease in thermal inversions. The fitted line between change in GDP and thermal inversions are almost horizontal, with an R-squared of 0.0007. Based on Figs. 2 and 3 we conclude that GDP and thermal inversions are essentially unrelated, in both national and county levels.

To ensure that our instrument meets the exclusion restriction criteria, we control flexibly for weather variables so that thermal inversions only affect body weight through air pollution. Thermal inversions have been used as IV for short-run air pollution (days and weeks) in Arceo et al. (2016), Chen et al. (2018), and Jans et al. (2018) and medium-run air pollution (months and years) in Chen et al. (2017) and Fu et al. (2017).

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

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

$$P_{ict} = \alpha_0 + \alpha_1 I_{ict} + f(W_{ict}) + \gamma_i + \sigma_t + u_{ict} \tag{2}$$

In the model, Y_{ict} denotes the body weight measures, including BMI, and indicators for overweight and obesity for individual i residing in county c at date t. We use P_{ict} to denote the average concentration of $PM_{2.5}$.[6] Note that we do not have a priori specified the exposure window—the period over which exposure to air pollution affects body weight, as there is no consensus from the previous health science literature.[7] As a result, we vary the exposure window from one month to 18 months and let the data determine its appropriate length. We choose an exposure window of 12 months as a starting point as many paper in the literature on the health impacts of air pollution focus on annual outcomes. 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 a robustness check by excluding the current month when we construct the 12-month exposure window.[8]

We instrument P_{ict} using the number of thermal inversions, denoted by I_{ict}, in the same exposure window. We use $f(W_{ict})$ 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 location. 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 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[9] (two-digit code)[10] over the period of 1989–2015.[11] 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; Wang, 2013).

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

[5] The county-level GDP data are from the county statistical yearbook. They are only available from 1999, and covered 1842 counties. We do not replicate Fig. 3 for our sample counties (71 counties) because 31 of them do not have GDP data.

[6] Note that pollution and inversion data are at county-level, but all regression models are estimated at individual level to ensure the use of individual fixed effects.

[7] For example, Li et al. (2015) used a three-year exposure window, and Li et al. (2016) used a one-year exposure window.

[8] 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.

[9] The nine provinces are Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou. We only have eight provinces in our sample because the county identifier is not available in Heilongjiang.

[10] 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/.

[11] The years are 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015.

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 sample only includes adults. We define a person as overweight if BMI $\geq$ 25, and obese if BMI $\geq$ 30 (WHO, 2018a).[12]

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 NASA. The data are available at a 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[13] and 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 cover 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 m to 36,000 m. The data are available at 6-h 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 m) is higher than that of the first layer (110 m) for each 6-h 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 possible non-linear effects.

4.5. Summary statistics

Our final sample has 13,741 adult individuals from 71 counties/districts across eight provinces over 1989–2015. Fig. A1 in the Online Appendix plots the number of interviewees in each survey year. There were 3452 interviewees in 1989, and the number of interviewees increased to 7612 in 1991 and was relatively stable afterwards. Thus, our sample is an unbalanced panel. Fig. A2 in the Online Appendix shows the frequency of interviews per interviewee. A total of 3520 and 2296 were interviewed twice and thrice, respectively. Only 563 individuals are present throughout the entire sample period.

One concern is that pollution may induce people to move (Chen et al., 2017), which may 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. Given this very 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 (Fig. A3 in the Online Appendix). Thermal inversions also have a strong seasonality mainly because of climatic related factors. Fig. A4 in the Online Appendix plots the average monthly cumulative thermal inversions across months.[14] 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.

Table 1 reports the summary statistics from our estimation sample. 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 22.76 with a standard deviation of 3.37. The average BMI is 24.19 in 2015, which is close to the cutoff of 25 for overweight. Fig. 4 plots the histogram of BMI and shows that most observations are concentrated 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 23.00% and 2.83% during our sample period, with 38.48% and 5.83% respectively in 2015. The average body weight is 58.47 kg, and average height is 160.03 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 64.75 μg/m,[3] which are six times higher than the WHO standard of 10 μg/m^3 (WHO, 2006). The concentration varies from a minimum of 23.75 to a maximum 141.32, with a standard deviation of 26.99. The average annual cumulative inversion times are 267.95. Since the occurrence is determined at each 6-h period, the probability of having an inversion in the 6-h period is 267.95/(4*365) = 18.35%.

[12] 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.

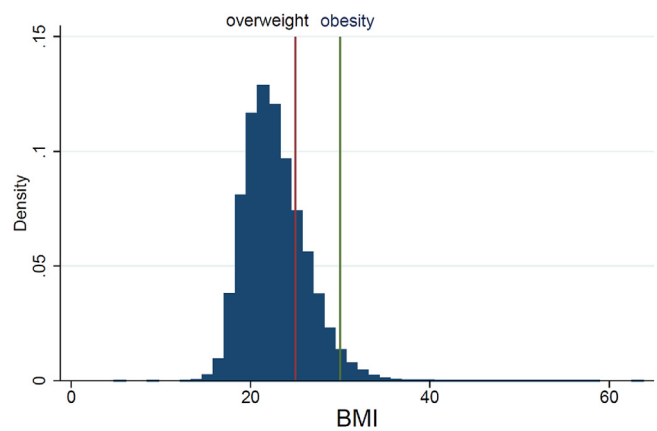
[13] The aggregation is conducted as follows. First, we downscale the original 50*60-km grid by five times using the bilinear method (Hijmans et al., 2015). This is because some counties are smaller than the 50*60-km grid. We then take the average for all downscaled grids within each county.

[14] For each dot, we sum all thermal inversions (determined with each 6-h period) in a given county and month, and then average over all counties in the same month.

Table 1
Summary statistics.

Variable	Description	N	Mean	SD	Min	Max
Body mass measure						
BMI	weight/height^2 (kg/m^2)	65,525	22.76	3.37	4.83	63.78
Percent Overweight	BMI $\geq$ 25	65,525	23.00	42.08	0	100
Percent Obese	BMI $\geq$ 30	65,525	2.83	16.59	0	100
Weight	kg	65,525	58.47	10.81	15	162.7
Height	cm	65,525	160.03	8.46	125	190
Male						
BMI	weight/height^2 (kg/m^2)	31,499	22.59	3.25	4.83	57.01
Percent Overweight	BMI $\geq$ 25	31,499	21.19	40.86	0	100
Percent Obese	BMI $\geq$ 30	31,499	2.22	14.72	0	100
Weight	kg	31,499	62.29	10.78	15	162.7
Height	cm	31,499	165.81	6.50	138.5	190
Female						
BMI	weight/height^2 (kg/m^2)	34,026	22.92	3.48	9.03	63.78
Percent Overweight	BMI $\geq$ 25	34,026	24.68	43.12	0	100
Percent Obese	BMI $\geq$ 30	34,026	3.41	18.14	0	100
Weight	kg	34,026	54.94	9.57	19.7	156.8
Height	cm	34,026	154.67	6.25	125	179
Air pollution						
$PM_{2.5}$	μg/m^3	65,525	64.75	26.99	23.75	141.32
Thermal inversions						
inversions	Times in 12 months (defined over 6-h intervals)	65,525	267.95	116.98	71	578

Notes: Unit of observation is individual-year. The survey covered 13,741 adult individuals (age $\geq$ 18) from 71 counties across eight provinces during 1989–2015 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 $\geq$ 25. Obesity is a dummy variable which equals one if BMI $\geq$ 30. $PM_{2.5}$ is average concentration in the 12-month exposure window. Thermal inversion is determined within each 6-h period, and then aggregated to the 12-month exposure window.



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 green line indicates the cutoff of 30, which is used to define obesity.

Fig. 4. Histogram of BMI in China during 1989–2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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 estimated first-stage coefficient 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 0.0288 μg/m^3 (0.04% of the mean), corresponding to an elasticity of 0.11.

Table 2
First-stage estimation: Effects of thermal inversions on $PM_{2.5}$.

	$PM_{2.5}$		
	(1)	(2)	(3)
Thermal inversions			
	0.0246***	0.0239***	0.0288***
	(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	15.02	14.08	21.62

Notes: $N = 65{,}525$. The dependent variable is average monthly $PM_{2.5}$ concentrations over the 12-month exposure window. Thermal inversions are aggregated from each 6-h 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). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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 for obesity in columns (5) and (6). Panel A reports the 2SLS estimates while Panel B reports the OLS estimates when air pollution is not instrumented. The specification in both panels and in all columns includes 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.

Table 3
Second-stage estimation: Effects of air pollution on body mass.

	BMI		Overweight		Obesity	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
$PM_{2.5}$	0.0422**	0.0625***	0.0061**	0.0082***	0.0021**	0.0027**
	(0.0213)	(0.0234)	(0.0027)	(0.0031)	(0.0010)	(0.0011)
KP *F-statistics*	23.59	21.62	23.59	21.62	23.59	21.62
Panel B: OLS						
$PM_{2.5}$	−0.0035	−0.0038	−0.0004	−0.0005	−0.0003	−0.0003
	(0.0037)	(0.0035)	(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: $N = 65{,}525$. 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 estimates, in which we use number of thermal inversions as an instrument for $PM_{2.5}$. Panel B reports the fixed-effect estimates in 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	Add county quadratic trends	No Weather Controls	Add individual and household controls	Exclude current Month	Alternative layers for IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: BMI							
$PM_{2.5}$	0.0625***	0.1003**	0.0658**	0.0778***	0.0660***	0.0632**	0.0734**
	(0.0234)	(0.0426)	(0.0276)	(0.0295)	(0.0243)	(0.0252)	(0.0298)
Panel B: Overweight (0/1)							
$PM_{2.5}$	0.0082***	0.0137**	0.0068*	0.0114***	0.0088***	0.0090**	0.0107***
	(0.0031)	(0.0058)	(0.0036)	(0.0043)	(0.0033)	(0.0035)	(0.0040)
Panel C: Obesity (0/1)							
$PM_{2.5}$	0.0027**	0.0039*	0.0017	0.0027**	0.0029**	0.0031**	0.0025*
	(0.0011)	(0.0020)	(0.0011)	(0.0013)	(0.0012)	(0.0013)	(0.0014)
KP *F*-statistics	21.62	12.56	27.84	14.08	20.84	18.58	13.92
Observations	65,525	65,525	65,525	65,525	63,487	65,525	65,525

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) controls for county-specific liner and quadratic time trends. Column (4) excludes weather controls. Column (5) includes controls for household expenditure and income, and dummies for employment and marital status. Column (6) excludes the current month to construct the exposure window. Column (7) changes the instrumental variables by coding thermal inversions with the temperature difference between the first (110 m) and the third layers (540 m). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Our preferred specification, column (2), shows that a 1 μg/m^3 (1.54%) increase in average $PM_{2.5}$ concentrations in the past 12 months increases BMI by 0.0625 units (0.27%). This corresponds to an elasticity between $PM_{2.5}$ and BMI of 0.18. 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 0.50 standard deviations.

Second, air pollution increases the probability of being overweight and obese. Columns (4) and (6) report that a 1 μg/m^3 increase in average $PM_{2.5}$ concentrations in the past 12 months increases the probability of being overweight by 0.82 percentage points, or 3.57 percent of the mean, and being obese by 0.27 percentage points, or 9.54 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 and obese by 0.53 and 0.44 standard deviations, respectively.

Third, 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 OLS estimates in Panel B are remarkably smaller in magnitude compared to the 2SLS estimates in Panel A. We believe the primary explanation is the measurement error of air pollution. Since we are using the outdoor air pollution constructed from satellite observations, we do not know the precise exposure of each individual. Many studies in the literature on air pollution effects have noted that assigning air pollution exposure to individuals from fixed monitors (or in our case satellites) will introduce classical measurement error (e.g., Currie and Neidell (2005), Schlenker and Reed Walker (2015), Arceo et al. (2016), and Knittel et al. (2016)). Classical measurement error in turn will lead to a downward biased estimate of the impact of air pollution.

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 are larger, but also less precise. In column (3), we return to year-by-month fixed effects and add county-specific linear and quadratic time trends. The estimates are qualitatively similar.

Our baseline model includes controls for 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 is essentially unchanged.

Table 4B
Robustness checks.

	Winsorize	Include pregnant women	Prefecture level	Only rural counties	Cutoff change	Body weight	Body height	Lead 12 months
	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: BMI								
$PM_{2.5}$	0.0566**	0.0595**	0.1036***	0.0442**	–	0.2012***	0.0464	0.1467
	(0.0219)	(0.0232)	(0.0333)	(0.0183)	–	(0.0646)	(0.0334)	(0.3172)
Panel B: Overweight (0/1)								
$PM_{2.5}$	0.0080**	0.0078**	0.0100***	0.0070***	0.0063**	–	–	−0.0022
	(0.0031)	(0.0031)	(0.0039)	(0.0026)	(0.0032)	–	–	(0.0188)
Panel C: Obesity (0/1)								
$PM_{2.5}$	0.0026**	0.0025**	0.0042***	0.0023**	0.0051**	–	–	0.0023
	(0.0011)	(0.0011)	(0.0016)	(0.0009)	(0.0020)	–	–	(0.0104)
KP *F*-statistics	21.66	21.72	16.99	26.89	21.62	21.62	21.62	0.45
Observations	64,803	66,324	65,525	46,133	65,525	65,525	65,525	65,525

Notes: Column (8) drops the top and bottom 0.5% observations of the BMI. Column (9) adds pregnant women to the sample. Column (10) collapses data at prefecture level, which usually includes 5 to 15 counties. Column (11) restricts the sample to rural counties, and exclude urban districts. Column (12) reports the estimates with new BMI cutoff of 24 for overweight and 28 for obesity. Columns (13)–(14) estimate the effect of air pollution on body weight and height separately. Column (15) uses the lead 12 months as the exposure window. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

In column (5), we add additional control variables, including log of household expenditures and income, job and marriage status. The estimates change little, suggesting that our instrument is not correlated with household economic conditions.[15] In Table A1 in the Online Appendix, we conduct placebo tests in which we use these controls as dependent variables. As expected, we then find insignificant impacts of air pollution.

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 (6), 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 (7) tests the robustness of our IV construction. In our baseline model, we define thermal inversions using the temperature difference between the first (110 m) and the second layers (320 layers). In column (7), we replace the second layer with the third layer (540 m). The results are very similar.

We then test the robustness of excluding extreme values of BMI from the sample in column (8) of Table 4B. Specifically, we winsorize the top and bottom 0.5% observations. After this, the maximum and minimum BMI are 33.53 and 16.08, in contrast to 63.78 and 9.03 before winsorizing.

Our baseline sample dropped pregnant women because their body weights largely increased during pregnancy and thus their BMI are not indicative for overweight and obesity. Nevertheless, we include these pregnant women in the estimation in column (9). Our estimates change little.

We construct the pollution exposure based on the county of residence. One concern is that people may reside in one county but work in another county. Unfortunately, the CHNS does not report the county of work place. We use two ways to address this concern. First, we collapse the data at prefecture level, which typically contains 5–15 counties. This captures any within-prefecture movement. It may be unlikely that people work and reside in different prefectures. The results are presented in column (10) and remain robust. Second, we only focus on rural counties, and exclude urban districts from the estimation, since people in rural counties are more likely to work and reside in the same county. Again, our results are robust, as shown in column (11).

The definitions for overweight (BMI $\geq$ 25) and obesity (BMI $\geq$ 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 31.67% and 7.09% respectively, larger than the WHO cutoff (23.00% and 2.83% respectively). Column (12) reports the estimates using the new standards. The effect on overweight is very similar to the baseline model. However, we find a much larger effect on obesity. This is intuitive because the mean obesity rate using the new cutoff is higher.

Our BMI measure is derived from body weight and height. In columns (13) and (14), 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 0.2012 kg, or 0.34% (mean = 58.47 kg).[16] On the contrary, the effect on body height is statistically insignificant. This provides a placebo test for confounders. Since our sample only includes adults (age $\geq$ 18), their body heights should not change in response to air pollution.

Finally, in column (15), we use the 12 months after the interview as the exposure window to conduct a falsification test. As expected, the estimates are insignificant, suggesting that unobserved secular trends do not confound our results.

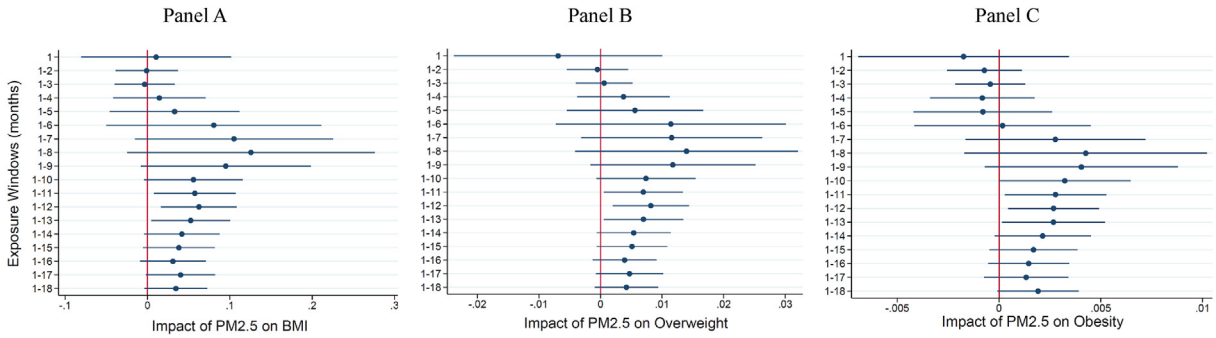
Table A2 in the Online Appendix reports the estimates under different assumptions on the clustering of the standard errors. Column (1) is the baseline model, with two-way clustering and clustered standard errors at the individual and county-year-month levels. In column (2), we keep the individual clustering 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 varying the exposure windows on our estimates of the impact of air pollution. The baseline model uses a 12-month exposure window. In Fig. 5, 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%

[15] We do not include these controls variables in our baseline model because they may be endogenous to air pollution.

[16] To better understand the impact on body weight, we also tested if the impact of air pollution on weight gain (as opposed to weight loss) and found the main pathway through which air pollution affects body weight is through weight gain.



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).

Fig. 5. Impacts of PM2.5 on Body Weight. N*otes:* 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).

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 (Figs. 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. Mechanism tests

Section 2 discussed several mechanisms through which air pollution may affect body weight. Although we cannot test the biological channel (slowing down the metabolism) with our data, we test several behavioral channels, including the amount of time in physical and sedentary activities, whether an individual walks to work or school, sleep time, and nutrition intake. Note that these behavioral responses were collected in reference to a short period (week or days) before the interview. However, our air pollution data are only available at monthly level. We thus use the reduced-form estimates, i.e., the regressions of thermal inversions on these behavioral responses in the corresponding exposure windows.[17] We also differentiate the response by urban and rural residents.

We start with physical activity in columns (1) to (3) in Table 5A. The survey asked how many minutes a respondent spent on Kung Fu, gymnastics, dancing, acrobatics, and sports in the past week. We regress time spent in physical activity on thermal inversions in the week prior to the interview, using the same controls in Equation (1). Since more than 90% of observations report zero minutes of physical activity, these estimates should be interpreted with caution. Nevertheless, we find a weakly negative effect of thermal inversion on physical activity for urban residents, but not for rural residents.

We then turn to sedentary activities in columns (4) to (6), which include minutes watching TV, playing computer games, reading, writing, and drawing in the past week. We do not find a statistically significant effect on sedentary activities for either urban or rural residents.

Next, we focus on an indicator for walking to work or school in columns (7) to (9). In particular, the dependent variable is whether an individual walked to work or school in past three days. We find that more inversions (higher pollution) significantly reduced the probability of walking to work/school for urban residents.

We then examine the effect of inversions on sleep time in columns (10) to (12) of Table 5B. We find that more thermal inversions lead to reduction in sleep time in the same day. This finding is consistent with Heyes and Zhu (2019), which also focuses on China using social media-based data. We find that the effect is mainly significant for rural residents. The insignificant although negative effect for urban residents may be due to a smaller sample size.

We next focus on food intake. The CHNS recorded detailed information on total calories consumed in different categories during past three days. In general, we find that air pollution increases fat intake for urban residents (column (17) of Table 5B).

To sum up, and given the data limitations highlighted above, we find that air pollution reduces minutes of physical activity, the probability of walking to work/school, hours of sleep, and increases fat intake. We also note that the above shorter-run (weeks) effects of thermal inversions on behavioral responses may not be the same as longer-run (months) effects. For example, people may make up lost exercises during a thermal inversion in a later week when air quality is better.[18]

6. Discussion

This paper documents a statistically significant and positive effect of air pollution on BMI, overweight, and obesity rates in China. In this section, we compare our estimates with those from two strands of the literature: those estimating the economic cost of air pollution and those estimating the causes of obesity. 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 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

[17] We present the reduced-form estimates on BMI in Table A3 in the Online Appendix.

[18] We also conduct a heterogeneity analysis but do not find significant difference across gender, age, education, and urban/rural residency.

Table 5A
Air pollution effects on activities.

	Activities						Walk to Work/School		
	Physical activity (past week)			Sedentary activity (past week)			(past 3 days)		
	mins			mins			yes/no (1/0)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full	Urban	Rural	Full	Urban	Rural	Full	Urban	Rural
Thermal inversions	−0.3521	−0.9347*	−0.2927	−0.4392	−0.6726	−0.3775	−0.0040	−0.0174***	−0.0016
	(0.2489)	(0.5637)	(0.2567)	(0.7474)	(1.7229)	(0.8154)	(0.0034)	(0.0059)	(0.0039)
Mean of Dep. Var.	17.64	32.61	11.61	312.20	376.28	286.52	0.51	0.40	0.54
Mean of Inversions	5.40	5.63	5.31	5.16	5.39	5.06	2.15	2.25	2.12
Observations	43,058	12,349	30,709	29,886	8548	21,338	16,395	3463	12,932
% of zeros	91.62	83.48	94.90	6.60	4.40	7.48	48.80	59.77	45.86
# of individual	10,512	3261	7251	8796	2661	6135	5463	1240	4223

Notes: The dependent variables are physical activities (minutes) in columns (1)–(3), sedentary activities (minutes) in columns (4)–(6) in the past week, and an indicator that equals 1 if an individual walked to work/school in columns (7)–(9) for past 3 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. Reduced-form regression models are estimated separately for a full sample and by urban and rural residents. The exposure window is past 7 days for physical and sedentary activities, and past 3 days for walk to work/school prior to the interview. 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). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5B
Air pollution effects on activities and nutrition intake.

	Sleep			Nutrition Intake					
	Bedtime (past day)			Carbo (past 3 days)			Fat (past 3 days)		
	hours			g			g		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Full	Urban	Rural	Full	Urban	Rural	Full	Urban	Rural
Thermal inversions	−0.0385**	−0.0062	−0.0534***	0.3913	−1.1846	0.6003	0.1342	0.9348**	−0.1590
	(0.0151)	(0.0275)	(0.0178)	(0.8315)	(1.3116)	(0.9130)	(0.2366)	(0.3716)	(0.2711)
Mean of Dep.Var	7.99	7.83	8.05	345.65	300.21	365.18	69.57	77.02	66.36
Mean of Thermal Inversions	0.77	0.76	0.77	2.32	2.34	2.31	2.32	2.34	2.31
Observations	31,062	8942	22,120	54,330	16,335	37,995	54,330	16,335	37,995
% of zeros	0	0	0	0	0	0	0	0	0
# of individual	9006	2737	6269	12,510	4143	8367	12,510	4143	8367

Notes: The dependent variables are bedtime in hours in the past day in columns (10)–(12), carbohydrate (grams) intake in columns (13)–(15), and fat (grams) intake in columns (16)–(18) for past three days. Reduced-form regression models are estimated separately for a full sample and by urban and rural residents. The exposure window is past 1 day for sleep and past 3 days for carbohydrate and fat intake prior to the interview. 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). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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 (2016) 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 3784 (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 0.82 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 1.64 (200*0.0082) on average, and a total health cost of CNY 1.89 billion (1.64*1.15 billion adults), or USD 0.27 billion on overweight and obesity-related medical costs.

We can also compare our estimates with previous studies that estimate the effect of $PM_{2.5}$ on other economic variables. Deryugina et al. (2019) find that a 1 μg/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 15 times larger than our estimate. Fu et al. (2017) and Chang et al. (2019) find that a 1 μg/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 11 and 26 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. In addition, 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 (2016) was calculated during the period of 2000–2009. Since the prevalence of overweight and obesity is increasing in China, the related medical cost will also be likely to increase in the future.

6.2. 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). We

compare our estimates with three prevalent studies that focus on important economic causes of obesity, including fast food restaurants, education, and peer and neighborhood effects.

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 smaller 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 0.27 percentage points, or 9.54 percent.

Second, we compare our estimates with Brunello et al. (2013), who investigate the effect of education on obesity in Europe. 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 1.55 (14.83/9.54) 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 in the U.S. This reduction is equivalent to reducing $PM_{2.5}$ concentrations by 17.78 μg/m.[3]

Note that the above studies focused on the U.S. and Europe, where the socioeconomic environment are very different from China, and thus the comparison should be interpreted accordingly. We can also compare our study to Aggarwak et al. (2019), who study how monetary incentives affect BMI through walking using field experiments in India. They find that the incentives program decreases the BMI by 0.052 units, or 0.20% (mean = 26.42). The magnitude is close to our estimate, in which we find that a 1 μg/m^3 decrease in $PM_{2.5}$ decreases the BMI for 0.0625 units, or 0.27% (mean = 22.76). In summary, we find that the impact of air pollution on obesity in China is of a magnitude that is meaningful and comparable to other economic causes.

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

There are a few limitations to our study that are worth emphasizing. 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, the body weight information is collected through an annual survey, which limits our ability to fully trace the potentially dynamic relationship between body weight and air pollution. Finally, data on behavioral responses pertain to a very short reference period of a few days to a few weeks.

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, since exposure to air pollution, and the behavioral and biological responses may be different across countries. We leave this for future research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2020.102461.

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