

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 $\mu\text{g}/\text{m}^3$ (1.54%) increase in average $\text{PM}_{2.5}$ concentrations in the past 12 months increases the body mass index by 0.27%, and also increases the overweight and obesity rates by 0.82 and 0.27 percentage points, respectively. We find evidence that these impacts can be explained by a variety of behavioral channels, including less physical activity, less walking to work/school, less sleep, and more fat intake.

JEL Codes: I12, I15, Q53

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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) \geq 25), while 11% of men and 15% of women worldwide were obese (BMI \geq 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 economics studies have sought to understand the complex and varied causes of obesity¹. This paper provides the first 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

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.

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 $\mu\text{g}/\text{m}^3$ (Panel A of Figure 1). In the same period, the prevalence of overweight and obesity has also increased rapidly. The average BMI increased by 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 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 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 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 inversions is a complex meteorological phenomenon and is typically independent of economic activities, as we demonstrate below. Importantly, we utilize the longitudinal

³ See detailed discussion in Section 2.

structure of our health survey data and include individual fixed effects. 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 and are subject to 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 significant 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 past one to three months.

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/school, and sleeping time. On the other hand, air pollution increases fat intake. This suggests that the 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 Walker, 2015; 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 $1 \mu\text{g}/\text{m}^3$ increase in average $\text{PM}_{2.5}$ 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, also plays 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 2,372 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.

3 Empirical Strategy

The primary empirical challenge for identifying the causal effect of air pollution on body weight 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, 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. If more high-caloric food are consumed than health investments as a result of an increase in income, then additional income will 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, 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 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. 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. Figure 2 illustrates this point by plotting annual GDP and the average annual cumulative thermal inversions in China over 1989–2015⁴. 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.

In Figure 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 2014⁵. 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 Figures 2 and 3 we conclude that GDP and thermal inversions are essentially unrelated, in both nation and county levels.

To ensure that our instrument meets the exclusion restriction criteria, we control for flexible weather variables so that thermal inversions only affect body

⁴ 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.

⁵ The county-level GDP data are from the county statistical yearbook. They are only available from 1999, and covered 1,842 counties. We do not replicate Figure 3 for our sample counties (71 counties) because 31 of them do not have GDP data.

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. (2018).

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

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

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

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, as there is no consensus from the previous health science literature⁷. In other words, we do not know how long an individual needs to be exposed to elevated levels of air pollution before it affects body weight. In this paper, we vary the exposure window from one month to 18 months and let the data determine the appropriate length of the exposure window. 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

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.

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 window⁸.

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 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.

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.

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 provinces⁹ (two-digit code)¹⁰ over the period of 1989–2015¹¹. 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

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.

selected from these communities. This dataset has been used in several previous studies (e.g., Wang, 2011 and 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 measured in kilograms (kg) divided by the square of the body height measured in square meters (m²). The unit of BMI is thus kg/m². Note that this formula only applies to adults aged 18 or above, and thus our sample only includes adults¹². We define a person is overweight if BMI \geq 25, and obese if BMI \geq 30 (WHO, 2018a)¹³.

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

¹² We do not focus on children because individual's birth month is not publicly available in CHNS, so overweight and obesity cannot be accurately measured using sex- and age-specific (in months) growth charts from CDC or WHO.

¹³ 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.

Buchard et al. (2016). We then aggregate from grid to county for each month¹⁴ 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 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

¹⁴ 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.

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. Figure A1 in the Online Appendix plots the number of interviewees in each survey year. There were 3,452 interviewees in 1989, and the number of interviewees increased to 7,612 in 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 3,520 and 2,296 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) and thus bias our estimates. Note that the individual fixed effects should absorb all initial sorting into different 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 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 months¹⁵. 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

¹⁵ 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.

include year-by-month fixed effects, which control for the unobserved shocks specific to particular year-month combinations.

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 22.76 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. Figure 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 $\mu\text{g}/\text{m}^3$, which are six times higher than the WHO standard of ten $\mu\text{g}/\text{m}^3$ (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 six-hour period, the probability of having an inversion in the six-hour period is $267.95/(4*365)=18.35\%$.

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 $0.0288 \mu\text{g}/\text{m}^3$ (0.04% of the mean), corresponding to an elasticity of 0.11.

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 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 $1 \mu\text{g}/\text{m}^3$ (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 $1 \mu\text{g}/\text{m}^3$ 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. 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 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 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.

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 conditions¹⁶. In Table A1 in the Online Appendix, we conduct placebo tests in which we use these controls as dependent variables. As expected, we 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 meters) and the second layers (320 layers). In column (7), 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 (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.

¹⁶ We do not include these controls variables in our baseline model because they may be endogenous to air pollution.

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 $1 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ concentrations increases the body weight by 0.2012 kg, or 0.34% (mean=58.47 kg). On the contrary, the effect on body height is statistically insignificant. This provides a placebo test for confounders. Since our sample only includes adults ($\text{age} \geq 18$), 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 different exposure windows. The baseline model uses a 12-month exposure window. In Figure 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% 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 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), 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., regress thermal inversions on these behavior responses in the corresponding exposure windows¹⁷. 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

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

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/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) 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, we find that air pollution reduces minutes of physical activity, the probability of walking to work/school, hours of sleep, and increases fat intake. These

behaviors could increase calorie intake while decrease calorie consumption, and eventually lead to an increased likelihood of overweight and obesity.

5.6 Heterogeneity analysis

In this section, we conduct a series of heterogeneity analysis by gender, age, education, and urban/rural residency. To show whether there is a statistically significant difference between subgroups, we interact the dummy or categorical variable for subgroups with thermal inversions. We do not interact with air pollution because we only have one instrumental variable, which is insufficient to instrument both air pollution and the interaction term.

Table 6 reports the point estimates and standard errors. For brevity, we only report estimates where BMI is the dependent variable. In column (1), we interact inversions with a dummy variable, which equals 1 for male and 0 for female. In column (2), we interact inversions with age, which is a continuous variable. We then interact inversions with education, which is measured by 7 categories, with the larger number indicating higher education in column (3). In the last column, we interact inversions with a dummy variable, which equals 1 for urban residents and 0 for rural residents. Overall, we do not find statistically significant difference on the effect of inversion/pollution across gender, age, education, and urban/rural residency.

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 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 $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ 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 $1 \mu\text{g}/\text{m}^3$ increase in average $\text{PM}_{2.5}$ 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 $\mu\text{g}/\text{m}^3$ 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 $\mu\text{g}/\text{m}^3$ 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 (2015) 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. Since these studies focused on the U.S. and Europe while we focus on China, the comparison is only suggestive.

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 $1 \mu\text{g}/\text{m}^3$, as we find that a $1 \mu\text{g}/\text{m}^3$ 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) $\mu\text{g}/\text{m}^3$.

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 $\mu\text{g}/\text{m}^3$. In summary, we find that the impact of air pollution on obesity in China is meaningful and comparable to other economic causes.

6.3 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 one caveat exists in our study. 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 PM₁₀, CO, and O₃ (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.

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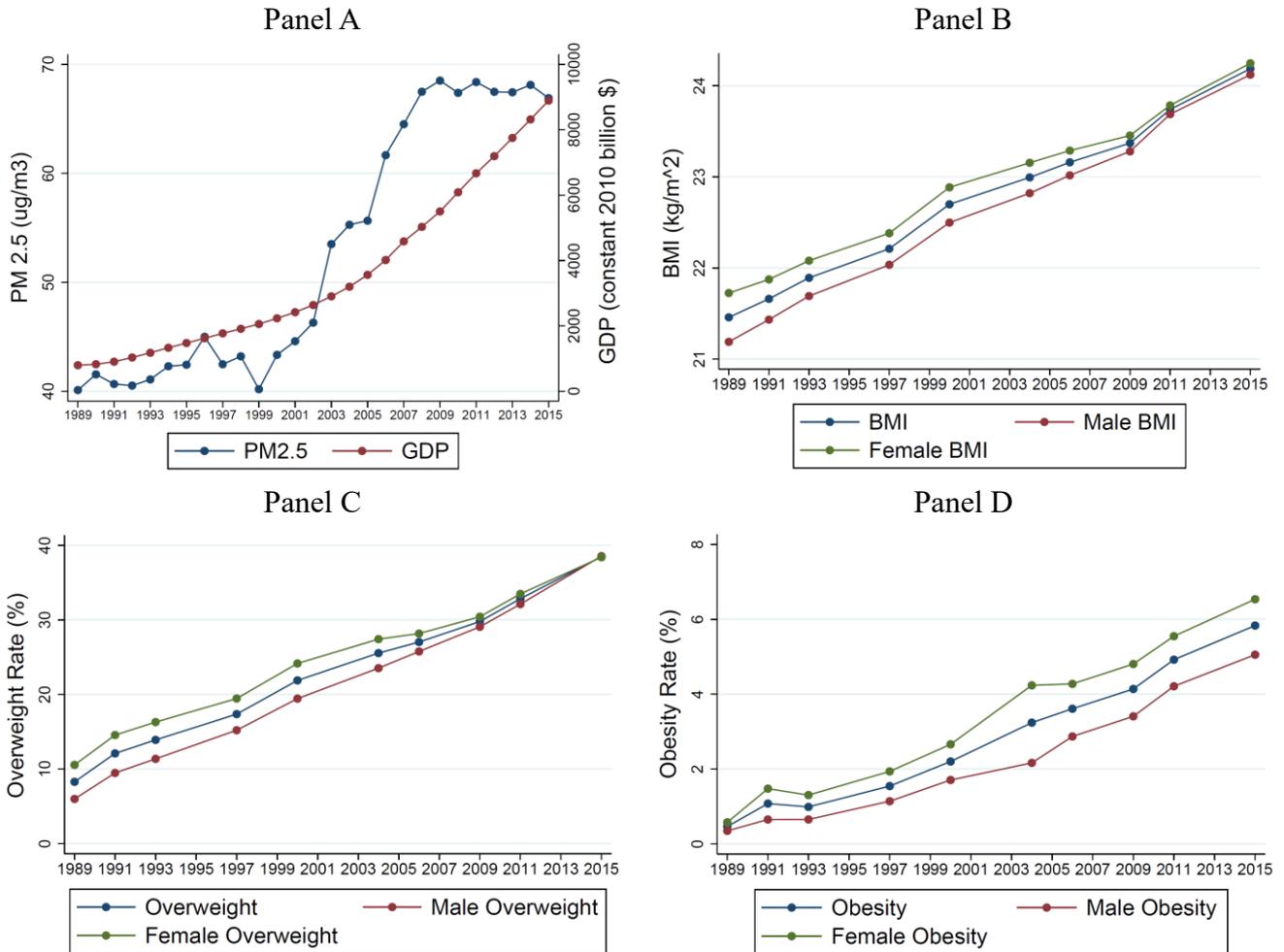
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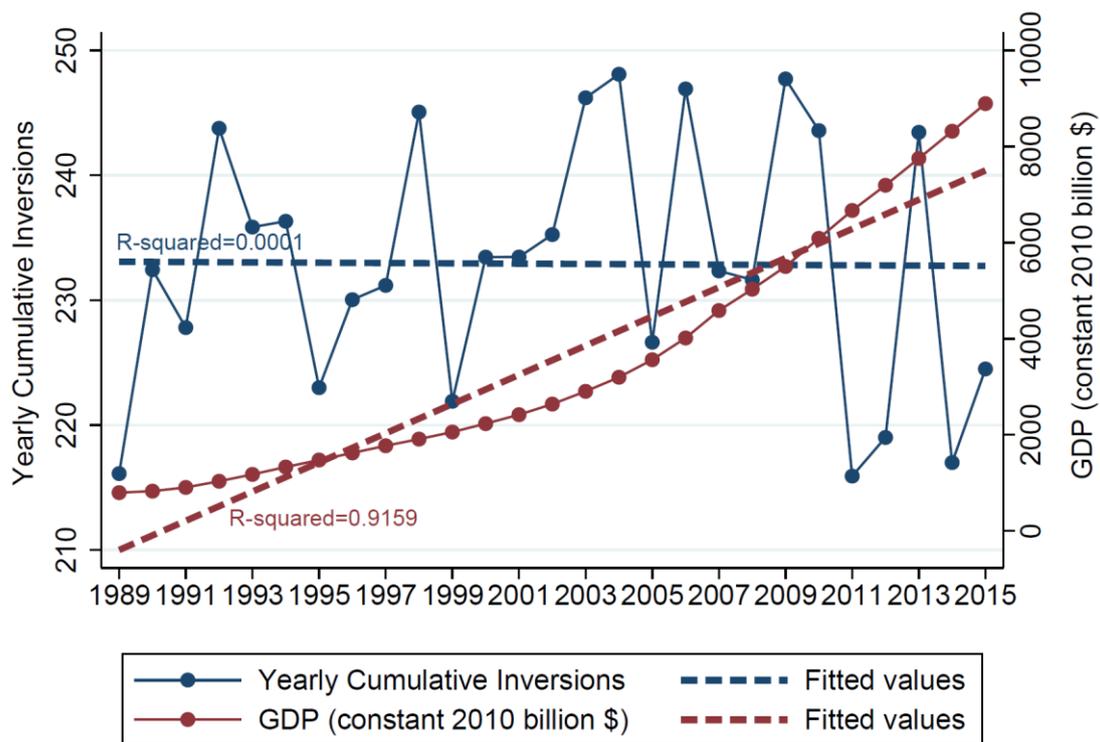
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Figure 1. Trends of PM_{2.5}, GDP, and Body Weight in China during 1989–2015



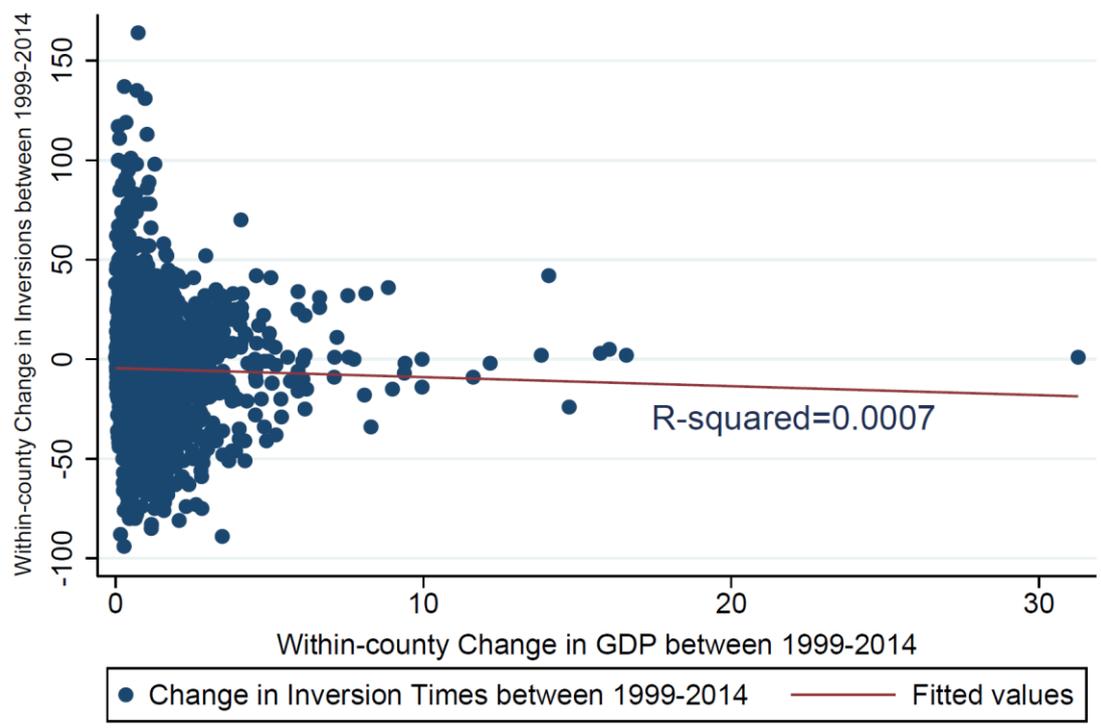
Notes: This figure shows the annual average of PM_{2.5} concentrations and GDP (Panel A), average BMI (Panel B), the prevalence of overweight (BMI \geq 25, Panel C), and obesity (BMI \geq 30, Panel D) for adults (age \geq 18) in China during 1989-2015. The data on GDP are from the National Bureau of 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.

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



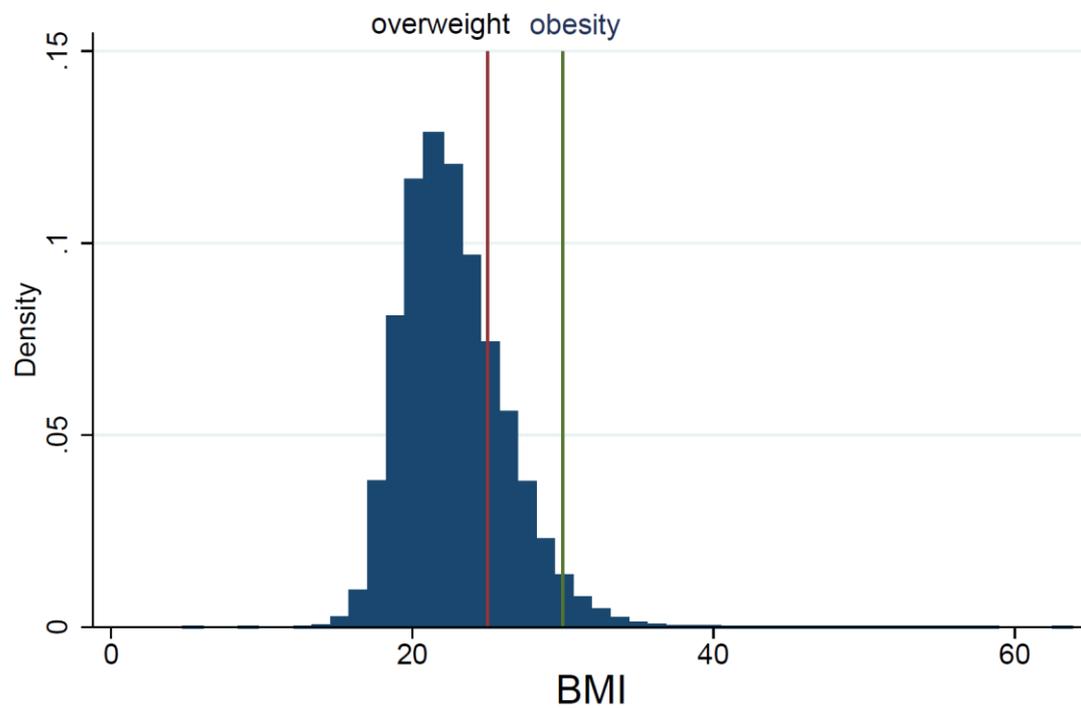
Notes: This figure shows the national trends of thermal inversion and GDP between 1989 and 2015. GDP is deflated to 2010 constant dollars.

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



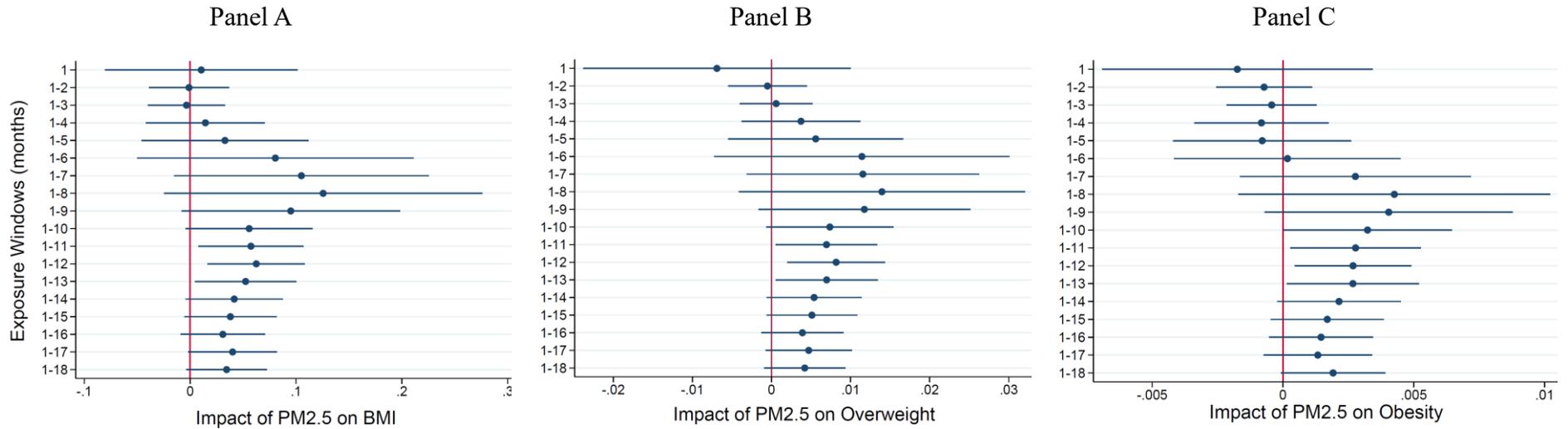
Notes: This figure plots the within-county change in GDP and thermal inversions in China between 1999 and 2014. GDP is deflated to 1999 constant billion dollars.

Figure 4. Histogram of BMI in China during 1989–2015



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.

Figure 5. Impacts of PM_{2.5} on Body Weight



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).

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}	$\mu\text{g}/\text{m}^3$	65,525	64.75	26.99	23.75	141.32
Thermal inversions						
inversions	Times in 12 months (defined over 6-hour 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 (m²). 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 six-hour period, and then aggregated to the 12-month exposure window.

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

	PM _{2.5}		
	(1)	(2)	(3)
Thermal inversions	0.0246*** (0.0064)	0.0239*** (0.0064)	0.0288*** (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 <i>F</i> -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-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		Obesity	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
PM _{2.5}	0.0422** (0.0213)	0.0625*** (0.0234)	0.0061** (0.0027)	0.0082*** (0.0031)	0.0021** (0.0010)	0.0027** (0.0011)
KP <i>F</i> -statistics	23.59	21.62	23.59	21.62	23.59	21.62
Panel B: OLS						
PM _{2.5}	-0.0035 (0.0037)	-0.0038 (0.0035)	-0.0004 (0.0005)	-0.0005 (0.0005)	-0.0003 (0.0002)	-0.0003 (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*** (0.0234)	0.1003** (0.0426)	0.0658** (0.0276)	0.0778*** (0.0295)	0.0660*** (0.0243)	0.0632** (0.0252)	0.0734** (0.0298)
Panel B: Overweight (0/1)							
PM _{2.5}	0.0082*** (0.0031)	0.0137** (0.0058)	0.0068* (0.0036)	0.0114*** (0.0043)	0.0088*** (0.0033)	0.0090** (0.0035)	0.0107*** (0.0040)
Panel C: Obesity (0/1)							
PM _{2.5}	0.0027** (0.0011)	0.0039* (0.0020)	0.0017 (0.0011)	0.0027** (0.0013)	0.0029** (0.0012)	0.0031** (0.0013)	0.0025* (0.0014)
KP <i>F</i> -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 linear 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 meters) and the third layers (540 meters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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** (0.0219)	0.0595** (0.0232)	0.1036*** (0.0333)	0.0442** (0.0183)	- -	0.2012*** (0.0646)	0.0464 (0.0334)	0.1467 (0.3172)
Panel B: Overweight (0/1)								
PM _{2.5}	0.0080** (0.0031)	0.0078** (0.0031)	0.0100*** (0.0039)	0.0070*** (0.0026)	0.0063** (0.0032)	- -	- -	-0.0022 (0.0188)
Panel C: Obesity (0/1)								
PM _{2.5}	0.0026** (0.0011)	0.0025** (0.0011)	0.0042*** (0.0016)	0.0023** (0.0009)	0.0051** (0.0020)	- -	- -	0.0023 (0.0104)
KP <i>F</i> -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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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) Full	(2) Urban	(3) Rural	(4) Full	(5) Urban	(6) Rural	(7) Full	(8) Urban	(9) Rural
Thermal inversions	-0.3521 (0.2489)	-0.9347* (0.5637)	-0.2927 (0.2567)	-0.4392 (0.7474)	-0.6726 (1.7229)	-0.3775 (0.8154)	-0.0040 (0.0034)	-0.0174*** (0.0059)	-0.0016 (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	8,548	21,338	16,395	3,463	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	3,261	7,251	8,796	2,661	6,135	5,463	1,240	4,223

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) hours			Carbo (past 3 days) g			Fat (past 3 days) g		
	(10) Full	(11) Urban	(12) Rural	(13) Full	(14) Urban	(15) Rural	(16) Full	(17) Urban	(18) Rural
Thermal inversions	-0.0385** (0.0151)	-0.0062 (0.0275)	-0.0534*** (0.0178)	0.3913 (0.8315)	-1.1846 (1.3116)	0.6003 (0.9130)	0.1342 (0.2366)	0.9348** (0.3716)	-0.1590 (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	8,942	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	9,006	2,737	6,269	12,510	4,143	8,367	12,510	4,143	8,367

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). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

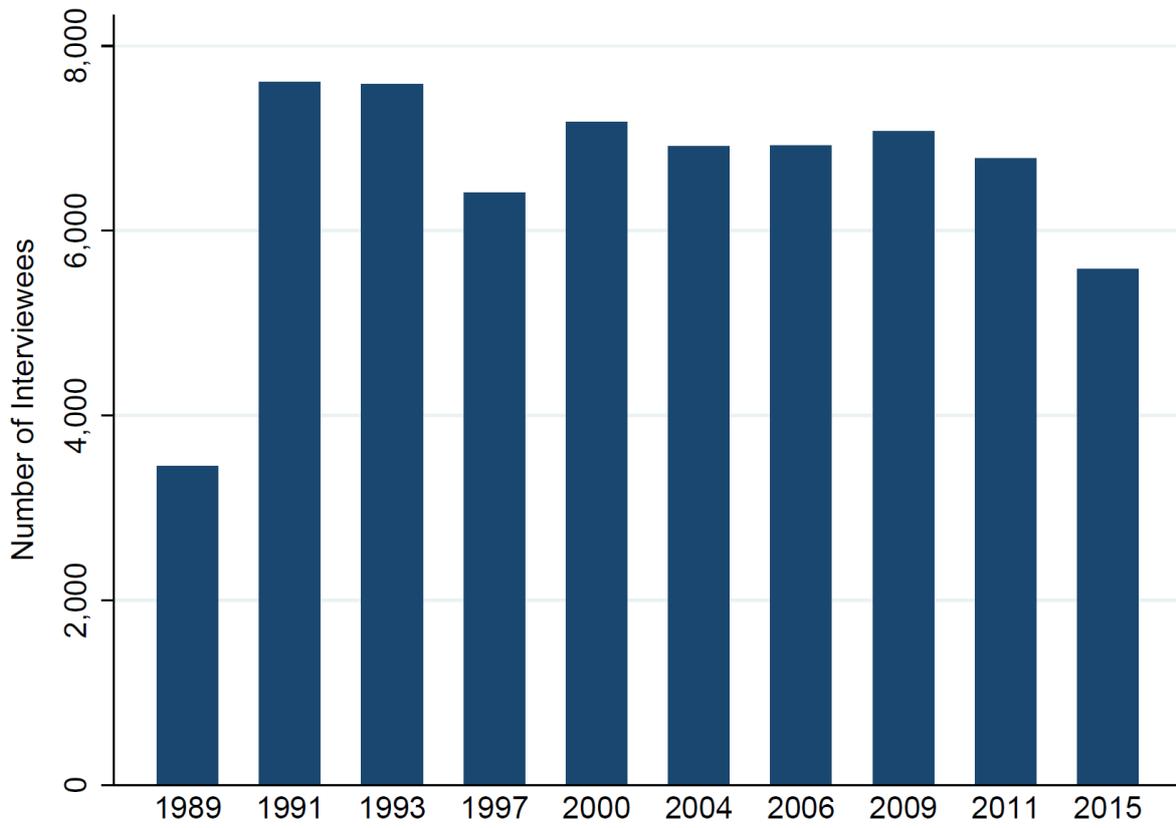
Table 6. Heterogeneity Analysis

	BMI			
	(1)	(2)	(3)	(4)
Inversions	0.0014 (0.0011)			
Male * Inversions	0.0003 (0.0006)			
Inversions		0.0021* (0.0011)		
Age * Inversions		-0.0000 (0.0000)		
Inversions			0.0016** (0.0006)	
Education * Inversions			0.0002 (0.0002)	
Inversions				0.0014** (0.0006)
Urban * Inversions				0.0015 (0.0009)
Observations	65,525	65,525	63,627	65,525
R-squared	0.1747	0.1747	0.1740	0.1747
Individual FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes

Notes: The dependent variable is BMI. Column (1) contains a dummy of gender (equals 1 if an individual is male) and an interaction between male and inversions. Column (2) contains individual's age and an interaction between age and inversions. Column (3) contains individual's education level (0: no school; 1: primary school; 2: junior high school; 3: high school; 4: technical or vocational school; 5: college or university; 6: master or above) and an interaction term for education and an interaction between education and inversions. Column (4) contains a dummy of residency (equals 1 if an individual lives in urban areas) and an interaction term between residency and inversions. 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). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

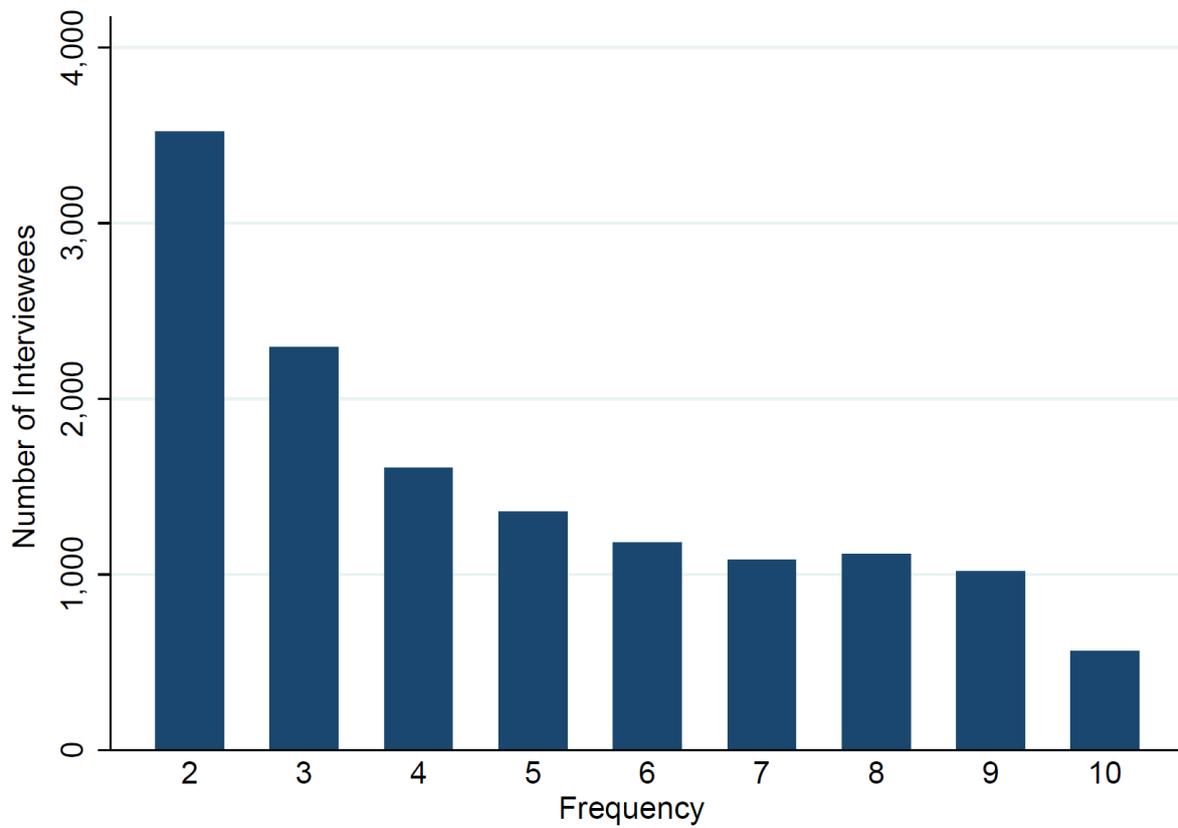
Online Appendix

Figure A1. Number of Interviewees across Years



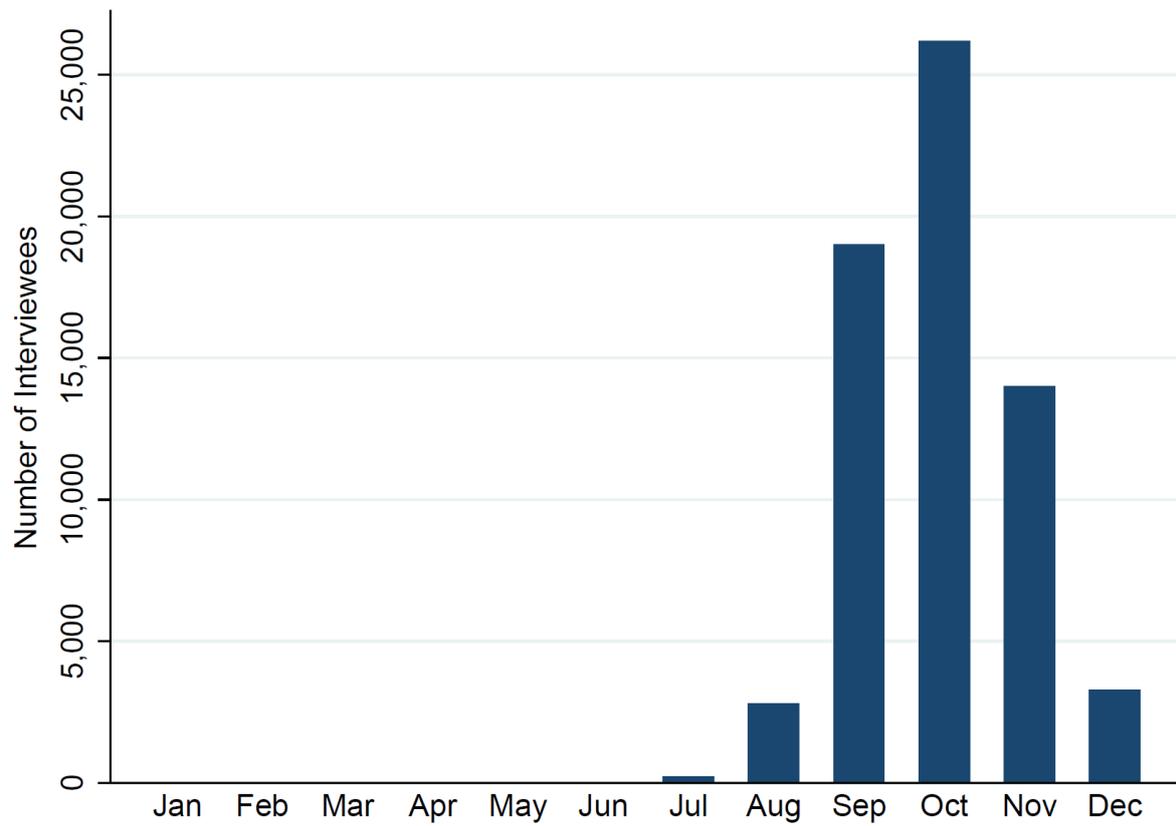
Notes: This figure plots the number of interviewees in each survey year (1989–2015).

Figure A2. Frequency of Interviewees



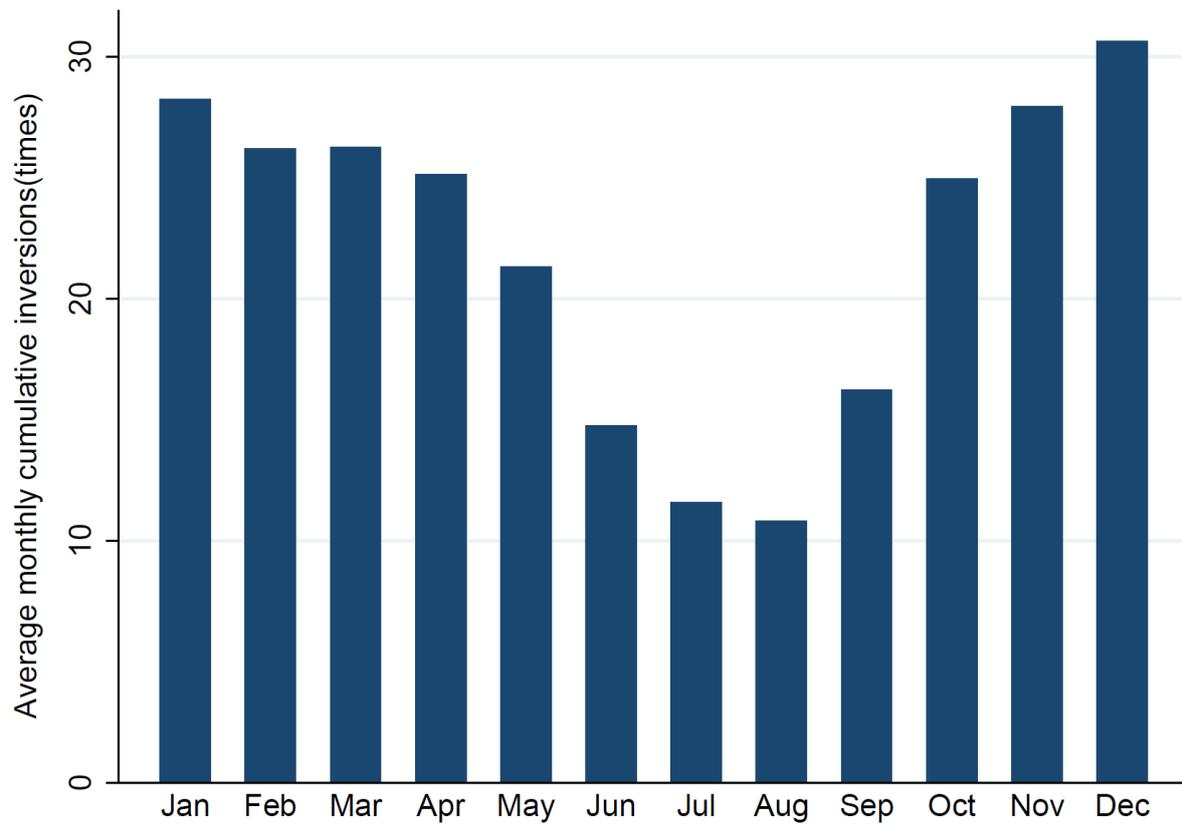
Notes: This figure plots the frequency in years for number of interviewees.

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. Effects of Air Pollution on Log of Household Income and Expenditure, and Individual Employment and Marital Status

	Log HH income	Log HH expenditure	If employed	If married
	(1)	(2)	(3)	(4)
PM _{2.5}	0.0132 (0.0174)	0.0414 (0.0387)	0.0025 (0.0053)	-0.0028 (0.0021)
Individual FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
KP <i>F</i> -statistic	21.90	21.84	21.49	20.84
Observations	64,461	64,690	65,288	64,872

Notes: The dependent variables are log of household income in column (1), log of household expenditure in column (2), if employed in column (3), and if married in column (4). 2SLS estimates are reported, in which we use number of thermal inversions as an instrument for PM_{2.5}. 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 A2. 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: County-year	One-way: County
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: BMI						
PM _{2.5}	0.0625*** (0.0234)	0.0625*** (0.0239)	0.0625** (0.0298)	0.0625** (0.0268)	0.0625** (0.0258)	0.0625** (0.0298)
Panel B: Overweight (0/1)						
PM _{2.5}	0.0082*** (0.0031)	0.0082** (0.0033)	0.0082** (0.0036)	0.0082** (0.0029)	0.0082** (0.0035)	0.0082** (0.0036)
Panel C: Obesity (0/1)						
PM _{2.5}	0.0027** (0.0011)	0.0027** (0.0011)	0.0027** (0.0011)	0.0027** (0.0010)	0.0027** (0.0012)	0.0027** (0.0011)
KP <i>F</i> -statistics	21.62	19.10	12.57	11.18	15.16	12.57

Notes: $N=65,525$. 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 A3. Reduced-Form Estimation: Effects of Thermal Inversions on Body Mass

	BMI		Overweight		Obesity	
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal Inversions	0.0013** (0.0006)	0.0018*** (0.0005)	0.0002** (0.0001)	0.0002*** (0.0001)	0.0001** (0.0000)	0.0001*** (0.0000)
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). 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). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.