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ABSTRACT

This paper looks at the effects of air pollution on migration in China using changes in the average strength of thermal inversions over five-year periods as a source of exogenous variation for medium-run air pollution levels. Our findings suggest that air pollution is responsible for large changes in inflows and outflows of migration in China. More specifically, we find that independent changes in air pollution of the magnitude that occurred in China in the course of our study (between 1996 and 2010) are capable of reducing floating migration inflows by 50 percent and of reducing population through net outmigration by 5 percent in a given county. We find that these inflows are primarily driven by well educated people at the beginning of their professional careers, leading to substantial changes in the sociodemographic composition of the population and labor force of Chinese counties. Our results are robust to different specifications, including simple counts of inversions as instruments, different weather controls, and different forms of error variance.

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1 Introduction

Air pollution has been shown to have causal impacts along an array of health and economic dimensions. A recent boom in the literature of air pollution has spurred a number of studies in economics that have used quasi-experimental methods to measure how short-run exposure to air pollution can impact infant mortality, adult mortality, hospitalization rates, health expenditures, hours worked, labor productivity, labor market decisions and test scores (Chay and Greenstone, 2003; Currie et al., 2009; Deschenes, Greenstone, and Shapiro, 2012; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Arceo, Hanna, and Oliva, 2016; Borgschulte and Molitor, 2016; Deryugina et al., 2016; Schlenker and Walker, 2016). A few studies have also shed light on the effect of medium and long run exposure to air pollution (Chen et al., 2013; Anderson, 2015) as well as long-run impacts of in-utero exposure (Adhvaryu et al., 2016; Molina, 2016). Many of these studies have been done in middle-income countries, in some of which air pollution is now considered the biggest environmental risk to human health.

Taken together, these results suggest that the total cost of air pollution is quite large as a share of income per-capita, although a formal aggregation exercise is difficult due to differences in context, methodologies and pollutant measures across studies.[1] Some studies have estimated the marginal willingness to pay (MWTP) to avoid air pollution for the US through hedonic methods (Chay and Greenstone, 2005). Provided that individuals are free to move across locations, and therefore house values capitalize local amenities, this measure is likely to reflect all costs of air pollution that are known to individuals (Roback, 1982; Sanders et al., 2011). Costs associated with re-location might cause hedonic estimates to deviate from the willingness to pay for air pollution (Bayer, Keohane, and Timmins, 2009). In addition, housing markets and location decisions in the developing world are often heavily regulated, causing further departures from the assumptions underlying hedonic methods.

[1] An aggregation of impacts across studies has been done for the economic cost of carbon emissions (Hsiang et al., 2017).

This is especially salient in China, where migration decisions have been heavily constrained by the hukou system (Kinnan, Wang, and Wang, 2016). However, the perception of air pollution costs is still likely to be reflected in the key economic decisions behind hedonic methods: re-location and migration. Studying how migration decisions are affected by pollution in the developing world offers us a window to the scope of the air-pollution costs that are internalized by the population. Second, studying the heterogeneity in migration flows across socioeconomic groups can help us better understand how the willingness to pay for air pollution might differ by education and income; but also how pollution-related migration might change the composition of the labor force across cities (Hanlon, 2016; Heblich, Trew, and Yanos, 2016). Third, a sizable literature has been devoted to the factors that determine migration decisions (Borjas, 1999, 2015). In this literature, the emphasis has been placed on traditional economic factors, such as income, wages, and networks (Clark, Hatton, and Williamson, 2007; Pedersen, Pytlikova, and Smith, 2008; Kinnan, Wang, and Wang, 2016). Although recent literature has paid more attention to environmental factors, most of these studies focus on weather (Feng, Krueger, and Oppenheimer, 2010; Feng, Oppenheimer, and Schlenker, 2015; Cai et al., 2016; Jessoe, Manning, and Taylor, 2016).

Our main contribution to this literature is the estimation of causal effects of air pollution on migration flows in China. The empirical challenges associated with studying migration responses to air pollution are two. First, as migration is a complicated and costly process, it is likely to respond slowly (over a number of months or even years) to air pollution exposure. Thus, the empirical challenges of estimating the causal effects of air pollution on migration are similar to the challenges of estimating any mid to long-run impact of air pollution: exogenous cross-sectional or mid-run variation in air pollution is hard to come by. In its absence, estimates are prone to be confounded by unmeasured joint determinants of air pollution and migration. For example, economic activity, which has been shown to attract immigrants (Borjas, 1999; Clark, Hatton, and Williamson, 2007), is also highly correlated with air pollution. Thus, as we demonstrate in this paper, an OLS regression of migration on air pollution yields a coefficient that could be (wrongly) interpreted as pollution attracting immigrants. The second challenge has to do with data constraints when studying migration decisions. Data that can track individual's locations over time is hard to come by at the scale that would be required to pick-up responses of migration to air-pollution.

Our approach to overcome the first empirical challenge is to use five-year variation in the average strength of thermal inversions within counties. Thermal inversions have been previously used to study short-run effects of air pollution on infant and adult mortality (Jans, Johansson, and Nilsson, 2014; Hicks, Marsh, and Oliva, 2015; Arceo, Hanna, and Oliva, 2016) and labor productivity (Fu, Viard, and Zhang, 2017). In relatively short periods of time and over small regions, thermal inversions cannot be used to study mid-run impacts of air pollution as the patterns within valleys are relatively stable (Hicks, Marsh, and Oliva, 2015). However, thermal inversion patterns do change slowly over a number of years and these changes can be different across regions of a large country such as China. For example, we find that many provinces in China experience differences of up to 150 thermal inversions across the three different five-year periods that we observe. Importantly, some regions may see thermal inversions increasing over time, both in terms of its frequency and average strength, while others may see reductions in the counts and average strength of thermal inversions over five year periods. Thus, the sheer size and regional diversity in China allows us to use longitudinal variation in the strength and frequency of thermal inversions as an instrument for air pollution to explore responses of mid-term outcomes such as migration. Although this source of variation in air pollution is certainly not permanent, decomposing the rapid changes in air pollution into permanent and transitory is impossible without a weather model. Thus, for the casual observer, medium-run changes in air pollution are likely used to update beliefs about the air pollution in the area going forward regardless of their source. We overcome the second challenge by integrating aggregated and individual-level information from the Population Census in China in order to construct five-year flows of migration at the county level between 1995 and 2010.

Another innovation of our paper is the use of satellite-based particulate matter with a diameter of less than 2.5 µm ($PM_{2.5}$) and sulfur dioxide (SO_2) data in economics. Although satellite-based proxies for air pollution have been used in the past (Kumar et al., 2011), it is not until recently that $PM_{2.5}$ and SO_2 model-based measures that incorporate Aerosol Optical Depth (AOD) measures but also historical analysis of the hydrological cycle as inputs, have been successfully validated vs. ground monitors in the atmospheric literature (Buchard et al., 2016). This allows us to fully exploit the wide availability of thermal inversions data (also from re-analysis models) for remote as well as urban areas in China without compromising the interpretability of our results.

Our findings suggest that air pollution is responsible for large changes in inflows and outflows of migration in China. More specifically, we find that independent changes in air pollution of the magnitude that occurred in China in the course of our study (between 1996 and 2010) are capable of reducing floating migration inflows by 50 percent and of reducing population through net outmigration by 5.3 percent in a given county. We find that these inflows are primarily driven by well educated people at the beginning of their professional careers, leading to substantial changes in the sociodemographic composition of the population and labor force of Chinese counties. We also find that females are more likely to migrate in response to air pollution, which is consistent with families living apart in order to protect young children. Our results are robust to different specifications, including simple counts of inversions as instruments, different weather controls, and different forms of error variance.

The rest of the paper is organized as follows: Section 2 is a background section that describes migration regulations in China as well as the literature on pollution and decision making around pollution in the context of China. Section 3 discusses our empirical strategy as well as our data. Section 4 presents our results and Section 5 discusses the significance of our findings as well as future work.

2 Empirical Background

2.1 Migration and Household Registration System in China

Migration typically refers to the permanent or long-term changes of the place of residence. Unlike other countries in which people can usually migrate freely, China implements the Household Registration System (HRS), the so called hukou system. The hukou system keeps a record of legal address and family relations for every citizen from birth to death. Furthermore, it divides people into rural and urban citizens according to their parents or the place of birth, and those in the cities usually enjoy privileges of local employment, education, health care and social welfare. There are certain requirements for changing registered residence, such as owning a permanent house in the area where a person has migrated to, having a stable occupation and stable income, and having good education and talents.[2]

Therefore, there are two types of migrants in China. The first type is the floating population, which indicates migrants who move to the destination but with their hukou at the origin. The second type is the registered migrants who move the destination along with their hukou. In this paper, we have two measurements of migration. The first is an approximate net outmigration ratio over 5 years. Typically, the net outmigration ratio is defined as the percent of population leaving the county net of new arrivals and deaths within a given period (Passel, Van Hook, and Bean, 2004; Feng, Krueger, and Oppenheimer, 2010; Feng, Oppenheimer, and Schlenker, 2015). However, reliable data on deaths at the county level are not available for every year in China. Thus, we calculate outmigration ratios without subtracting deaths and subtracting approximate deaths.[3] The population in this measure is based on the physical presence of each individual in that county, and thus this measure has the advantage of including both floating and official migrants. The second measurement of migration flows we use is the destination-based floating immigration; or those who are

[2]See http://www.gov.cn/xinwen/2014-07/30/content_2727331.htm (in Chinese).

[3]Note that deaths may themselves be affected by air pollution. Thus, it is important to document the extent of this effect for the population we study in order to ensure that our estimates are not affected by this necessary omission. We discuss this at length in Section 3.2.

surveyed away from their hukou. Studying this measure of migration has multiple purposes: It allows us to check for the pull effect of air quality, i.e. whether individuals pay attention to recent pollution levels at their destination, which is informative about the level of sophistication in individual's moving decisions. Second, it serves as a one of the checks we perform on our net outmigration specification given that we can only net out approximate deaths. And third, it helps understand whether migration flows that respond to air pollution are solely driven by official migrants (i.e. those that officially change their hukou) or are also driven by floating migrants.

Figure 1 depicts the migration patterns for each county in China over the period 1996-2010. In Panel A, migration is measured by net outmigration ratio, which is defined as the percent of population leaving the county net of new arrivals and deaths. Positive net outmigration ratio, labelled in yellow, means that on net people leave that county. On the contrary, negative net outmigration ratio, labelled in blue, means that on net people move to that county. In general, the metropolitan areas especially three economic regions in China- the Yangtze River Delta (Shanghai, Jiangsu, Zhejiang), the Pearl River Delta (Guangdong), and the Jing-Jin-Ji Area (Beijing, Tianjin, Hebei) and other coastal areas –attract a large share of migrants. There are a few exceptions to this pattern in the northwest (the Xinjiang Uyghur Autonomous Region, Qinghai, Gansu, and the Inner Mongolia Autonomous Region) and the Tibet Autonomous Region, where income is lower but migrants are still drawn in potentially due to abundant natural resources and the China Western Development policy. Panel B shows the destination-based immigration ratio, which is defined as the percent of population entering the county with their hukou in the origin, in the same period. Light blue means low immigration ratio while dark blue means high immigration ratio. In general, one can observe a similar pattern as shown in Panel A: economic developed regions attract a significant share of the migrants.

2.2 Air Pollution in China and Avoidance Behavior

Over the past decades, air quality has increasingly deteriorated in China, causing increasing concern on China's public health and economic development (Ebenstein et al., 2015). Figure 2 plots the average concentration measured in microgram per cubic meter (μg/m^3) of the two primary air pollutants –$PM_{2.5}$ (in red in Panel A) and SO_2 (in blue in Panel B) –in China in each year over the period 1980-2015. Two red vertical lines highlight our study period: 1996-2010. The blue vertical line indicates the year of 2001, when China joined the World Trade Organization (WTO).

In general, the concentrations of both air pollutants have significantly increased over the period, in particular after 2001, when China became the world's factory. The concentration of $PM_{2.5}$ has increased from 30.98 μg/m^3 in 1980 to 66.90 μg/m^3 in 2015, which is almost 6 times than the National Ambient Air Quality Standard (NAAQS) made by the Environmental Protection Agency (EPA) in the US.[4] A similar pattern can be found for SO_2.

Figure 2 also plots the average strength of thermal inversions in Celsius degrees in China over the period 1980-2015.[5] In contrast to air pollutants, there is no a clear time trend of thermal inversion strength. This is especially important after 2001, when the steep increase in $PM_{2.5}$ and SO_2 was tied to rapid economic growth. This figure thus backs up the exogeneity assumption of our instrumental variable.

China has implemented several policies to reduce air pollution. For example, the State Council had implemented the Two Control Zone (TCZ) policy in January 1998 to reduce acid rain and SO_2 pollution. The legislation required prefectures exceeding national thresholds in either acid rain or SO_2 to take actions such as using clean coal for power plant to improve air quality. Overall, 175 out of 333 prefectures were mandated to reduce those two air pollutants. The drop in SO_2 after 1998, which is mainly due to the TCZ policy designated to reduce acid rain and SO_2 in 1998 (Hao et al., 2001). Studies show that this policy is effective in

[4] https://www.epa.gov/criteria-air-pollutants/naaqs-table.

[5] See Section 3.1 for a definition of thermal inversion strength.

reducing SO_2 emissions (Hao et al., 2001) and further reducing infant mortality (Tanaka, 2015).

In recent years, the particular matter (PM) has become a major environmental concern in China. On September 10th, 2013, the State Council has issued the "Air Pollution Prevention and Control Action Plan", which is regarded as the most aggressive and ambitious air quality management action plan in the history of China.[6] The plan aims at reducing air pollution. Specifically, by 2017 the urban concentration of particulate matter with a diameter of less than 10 μm (PM_{10}) shall decrease by 10% compared with 2012. Concentration of $PM_{2.5}$ in the Jing-Jin-Ji Area, Yangtze River Delta, and Pearl River Delta region shall respectively fall by around 25%, 20%, and 15%.

Even though most regions in China experienced increases in pollution between 1996 and 2010, regional policy differences as well as differences in meteorological conditions led to substantial heterogeneity in pollution changes over time. Figure 3 shows a map of local changes in pollution. As in our estimation we will be controlling for nation-wide changes as well as county fixed effects, this map is helpful to illustrate that there is a considerable amount of remaining variation in pollution. Out of this remaining variation, our IV strategy will ensure that we only use the one due to local variation in thermal inversion strength.

A large literature in both epidemiology and economics has documented important effects of air pollution on human health (see a review in Graff Zivin and Neidell (2013)). $PM_{2.5}$ can penetrate the thoracic region of the respiratory system, and cause the respiratory and cardiovascular diseases in the short term (hours and days). The long-term (months and years) exposure can increase mortality from both cardiovascular and respiratory diseases as well as from lung cancer (WHO, 2013). The short-run and long-run effects of $PM_{2.5}$ on human health have been well documented in various literatures (Dockery et al., 1993; Pope III and Dockery, 2006; EPA, 2009; Deryugina et al., 2016). SO_2, another major air pollutant in China, is also harmful for human health. When SO_2 is breathed in, the nose, throat, and

[6] http://english.mep.gov.cn/News_service/infocus/201309/t20130924_260707.htm

airways will be irritated and cause a variety of respiratory symptoms and decreased lung functioning (Linn et al., 1983, 1987; EPA, 2008).

Concerns about air pollution in China and elsewhere have been shown to motivate changes in behavior. Several studies have demonstrated that people engage in short-run avoidance behaviors such as staying indoors (Neidell, 2009) or purchasing particulate-filtering face-masks (Zhang and Mu, 2016) in a highly polluted day. Recent research has also shown that pollution concentrations can motivate medium-run investments such as home air purifiers (Ito and Zhang, 2016). Importantly, theory suggests that utility maximizing households will choose their avoidance behavior portfolio optimally such that marginal cost across all costly protective strategies is equalized across them and, in equilibrium, it is equal to their marginal benefit. Thus, migration decisions should be reflective of the cost families are willing to exert to avoid air pollution, and thus the marginal benefit of reducing it.

3 Empirical Strategy and Data

The goal of our empirical estimation is to capture the causal effect of mid-term pollution on migration. There are two important challenges in doing this. First, air pollution and economic activity are highly correlated. Thus, it is likely the case that those cities with high economic activity that attract immigrants by offering highly paid jobs are also those which experience high levels of air pollution. In fact, as we discuss in the results section, if one looks at the simple correlation between air pollution and immigration they appear positively correlated over time even when controlling for county fixed effects. These results should not be interpreted as air pollution attracting immigrants, as time-varying confounding factors (including economic activity) could be driving the correlation. Second, overcoming the first challenge requires finding a random source of variation for air pollution. However, most reliably exogenous determinants of air pollution in the literature provide short-run variation in air pollution (over the course of days, weeks or months). Migration, however, is an outcome that is likely to respond slowly to air pollution as it is akin to an investment decision in that is difficult to reverse and very costly. Thus, we expect individuals to react slowly to perceived permanent changes in air pollution, and importantly, to react to changes that are observable over long periods of time. Most sources of long-run variation in air pollution, such as changes in local policy or economic fluctuations in neighboring regions, are likely to have independent effects on migration as they may shift labor market conditions. The combination of these two issues pose an important challenge for identification as sources of permanent variation in air pollution that is not correlated with other sociodemographic or economic patterns are hard to find.

Our approach to overcoming this challenge is to use medium-run random variation in air pollution stemming from 5-year fluctuations in the strength of thermal inversions in a given county. Although this source of variation in air pollution is certainly not permanent, decomposing the rapid changes in air pollution into permanent and transitory is impossible without a weather model. Thus, for the casual observer, medium-run changes in air pollution are likely used to update beliefs about the air pollution in the area going forward regardless of their source.

3.1 Econometric Model

To estimate the causal effect of air pollution on migration, we propose to estimate the following 2SLS model

$$M_{ct} = \beta_0 + \beta_1 P_{ct} + f(W_{ct}) + \gamma_c + \sigma_t + \varepsilon_{ct} \tag{1}$$

$$P_{ct} = \alpha_0 + \alpha_1 TI_{ct} + f(W_{ct}) + \gamma_c + \sigma_t + \mu_{ct}, \tag{2}$$

where M_{ct} denotes the net outmigration ratio, which is the fraction of people leaving a county minus new arrivals and deaths, in county c and period t. We define each period as a 5-year interval. Thus, we have 3 periods in our study: 1996-2000 (period 1), 2001-2005 (period 2), and 2006-2010 (period 3).

The right-hand-side variable of interest in equation (1), P_{ct} , measures the 5-year average concentration of the two primary air pollutants: $PM_{2.5}$ and SO_2. We instrument air pollution with the strength of thermal inversions in the five year period, TI_{ct}, conditional on flexible functions of weather variables (W_{ct}), county fixed effects (γ_c), and period fixed effects (σ_t). TI_{ct} corresponds to the thermal inversion strength of six-hour periods in each county and period. The thermal inversion strength is defined using above-ground temperature minus ground temperature. A positive difference indicates the existence of a thermal inversion and the magnitude measures the inversion strength. A negative difference indicates the non-existence of a thermal inversion. We keep the positive difference and truncate the negative difference to zero within each six-hour period. The strength of inversions are then aggregated from each 6 hours to each year, and further averaged during each 5-year period. In Section 3.2 below we provide a detailed description of the source of information for thermal inversion as well as migration and pollution measures.

The idea to use thermal inversion as an instrumental variable for air pollution was first proposed by Arceo, Hanna, and Oliva (2016), to estimate the effect of air pollution on infant mortality in Mexico City. This identification strategy has been subsequently used to explore the short-run effects of air pollution on children's health in Sweden (Jans, Johansson, and Nilsson, 2014) and on adult mortality in the United States (Hicks, Marsh, and Oliva, 2015) and on manufacturing labor productivity in China (Fu, Viard, and Zhang, 2017). Thermal inversions are a common meteorological phenomenon that leads to higher concentrations of pollutants near the ground. The mechanism through which this occurs is the following: under normal conditions temperature decreases as altitude increases. Since air moves from hot to cool regions, air pollutants can circulate vertically decreasing air pollution concentrations near the ground. However, under certain meteorological circumstances (see Arceo, Hanna, and Oliva (2016)), the temperature of a layer of air above ground could be higher than that at lower altitudes, which leads to an inversion in the temperature/height gradient or *thermal* *inversion*. When this occurs, air pollutants are trapped near the ground leading to higher air pollution concentrations.

There are several facts about thermal inversions that are relevant for identification. First, although there is no plausible direct mechanism through which temperature above ground level could affect human health or human behavior, thermal inversions often coincide with weather patterns on ground level, and weather may have direct impacts on our outcome of interest (Feng, Krueger, and Oppenheimer, 2010; Feng, Oppenheimer, and Schlenker, 2015; Cai et al., 2016). To illustrate the relationship between thermal inversions and weather, Panel A of Appendix Figure A.7 shows that the national average of thermal inversion strength (solid line) is highest during very cold days. However, mild and very hot temperatures are also associated with strong thermal inversions. This national pattern, however, masks large variation in the relationship between thermal inversions and temperature across regions. To show this variation, Panels B, C and D of the same figure show the nonlinear relationship between temperature and inversion strength for Beijing, Shanghai and Guangzhou, respectively. The regional variation in the thermal inversion-temperature relationship stems from differences in the underlying nature of thermal inversions across regions. Strong thermal inversions during cold months are common in regions where inversions are predominantly radiative. Radiative inversions emerge when the effect of earth's warmth radiation on air near the ground causes large differences with air at higher altitudes. Other sources of thermal inversions (subsidence and advection) can cause thermal inversions in warmer months.

To address confounding issues stemming from the relationship between thermal inversions and weather, we control for very flexible functions of an array of weather measures at the ground level such as 1- Celsius degree daily temperature bins, and second degree polynomials in precipitation, sunshine duration, relative humidity, and wind speed.[7] Our identification strategy thus relies on the variation in the five-year average strength of thermal inversions net of weather variation at ground level.

[7]We also explore the sensitivity of our results to variations in the functional forms of weather variables such as region-specific temperature effects.

Second, there are some regions that are more prone to thermal inversions than others, which causes permanent differences in air pollution concentrations across regions. Figure 5 depicts the annual average concentration of $PM_{2.5}$ (in red) and SO_2 (in blue) over 1980-2015 for three categories of counties: counties with inversion strength less than 0.08°C (in circle), between 0.08 and 0.24°C (in rhombus), and above 0.24°C (in triangle). These thresholds were defined based on the 33_{rd} and 66_{th} percentile respectively. In general, air pollution is higher in counties with higher strength of thermal inversions. The average concentration of $PM_{2.5}$ for counties with less than 0.08°C is 38.2 µg/m^3, while is 50.0 µg/m^3 and 56.9 µg/m^3 for counties with 0.08-0.24°C and above 0.24°C strength, respectively. A similar pattern can be found for SO_2. These permanent differences in air pollution may induce self-selection patterns across regions that could potentially result in differences in migration rates. For example, if only healthy young adults are willing to live in highly polluted areas and young adults are more prone to relocating in response to good job opportunities, we could potentially observe that areas with a high average strength of thermal inversions have high migration rates. Thus, it is important for us to control for time-fixed differences in air pollution through county fixed effects. By doing so, we constrain the thermal inversion-related variation in air pollution we use to deviations from the within-county average strength of thermal inversions over the course of fifteen years. Figure 6 illustrates the variation that we are using. Each set of vertically aligned dots represents a province, while each dot represents the average inversion strength per year within each five year period for a particular province. The vertical distance between the dots of each set is similar to the variation that we use for this study (the variation we used is within counties, rather than within regions, and it is also net of period fixed effects and weather effects). Although there are large cross-sectional differences in the average strength of inversions, there is a considerable amount of variation over time within each region.

Finally, to guard against long-run trends in thermal inversions to coincide with macroeconomic trends, we include period fixed effects, σ_t. Figure 2 plots the average strength of thermal inversions (in black), concentrations of $PM_{2.5}$ (in red) and SO_2 (in blue) in each year from 1980 to 2015. Although it is clear from this figure that there is no consistent trend of thermal inversions over time, there appears to be a slight upward trend during the period of our study (1996-2010). As stated before, the level of air pollution has dramatically increased in the study period, especially after 2001 when China joined the WTO. Thus, it is important to control for overall trends that could pick-up some of the large changes in economic variables during this period.

Note several econometric specification details. First, we run regressions separately for $PM_{2.5}$ and SO_2 since we only have one IV. We discuss the multiple pollutant models in detail in Section 4.4. Second, standard errors are clustered at county level, to adjust for autocorrelation within each county over time periods. In the robustness check, we cluster standard errors at prefecture level, to account for potential within-prefecture correlation across counties and over periods.[8] Our results are still robust at 5% level. Lastly, all regression models are weighted by population to correct for heteroscedasticity, as large population differences across counties will lead to differences in the precision of calculated migration rates. Again, our results are robust without weighting.

3.2 Data Sources and Summary Statistics

3.2.1 Migration

As discussed in Section 2.1, there are two types of migrants in China: those who migrate to a new county but do not possess the local household registration, and those who migrate and possess the local household registration. The first type is referred as floating population or floating migration, while the second is regarded as registered migrants.

We use population and death counts from the Population Census in China to calculate two measures of migration: net outmigration flows of all types of migration and immigration flows

[8]Prefecture is the administrative level between province and county in China. In our sample, we have 31 provinces, 335 prefectures, and 2,649 counties.

of floating migrants. Since 1990, China has conducted decennial population census (Macro Census) in 1990, 2000, and 2010, and the 1% population sample survey (Micro Census) in 1995, 2005, and 2015. For our study, we use 1% and 20% individual-level data randomly drawn from the 2000 Macro Census and the 2005 Micro Census, and county-aggregated data in 1995 and 2010 from National Bureau of Statistics (NBS) of China.[9]

The first migration measure, the net outmigration ratio, is the percent of population leaving the county net of new arrivals and deaths. Since the population herein is based on individual's physical presence in that county, the net outmigration ratio essentially measures the migration of both floating and registered migrants. We use the residual approach to calculate net outmigration. The residual approach has been widely used in the previous literature (e.g., see Passel, Van Hook, and Bean (2004); Feng, Krueger, and Oppenheimer (2010); Feng, Oppenheimer, and Schlenker (2015)). In particular, we calculate the net outmigration ratio for people aged between 15 to 60, the bulk of the working force, during each 5-year interval using the following equation:

$$NetOutmig[15,60]_{c,t} = \frac{Pop[15,60]_{c,t} - Pop[20,65]_{c,t+5} - D[1\hat{5},60]}{Pop[15,60]_{c,t}} \times 100\%, \tag{3}$$

where $NetOutmig_{c,t}$ is the net outmigration ratio for those aged $[15, 60]$ during the 5-year interval starting from year t in county c; $Pop[15,60]_{c,t}$ indicates the total population aged $[15, 60]$ in county c at the beginning of the five-year interval that started in year t, while $Pop[20,65]_{c,t+5}$ denotes the population of the same cohort five years later, and $D[1\hat{5},60]$ represents an approximate measure of deaths for this same population during the 5-year interval. Below we explain the data constraints on deaths and our approach to ensure that these constraints do not affect our results.

Because NBS only surveys deaths during the survey year, we are not able to obtain the death counts in the whole five-year period. Thus, we compute an approximate net

[9]To the best of our knowledge, no individual-level census data in 1995 and 2010 has been made publicly available.

outmigration ratios in one of two ways. The first way omits deaths from calculation in equation (3). The second way approximates deaths in the five year period by multiplying deaths in the last year by five. Either option, omitting or only partially accounting for deaths in the five year period, creates measurement error of net outmigration ratio and will bias our estimates upwards if pollution is positively correlated with death counts. In order to evaluate the potential bias, we estimate the effect of air pollution on deaths for different age groups using the years for which deaths data are available (2000, 2005 and 2010). In order to do so, we estimate model in equations (1) and (2), with deaths in each of these years as the dependent variable and pollution in current year, past two years, past three years, past four years and past five years as the right hand side variable of interest. Results of this specification are shown in Tables A.10 and A.11. Each column reports results on a different age group. We find that air pollution exposure within the last four and five years has a positive and significant effect on current year deaths of total population (all ages), population under 15 years of age, and population above 60 years of age. However, we find that deaths among our population of interest, those between 15 and 60 years of age, show a small and not statistically significant response to air pollution. These findings across age groups are consistent with prior literature that has studied the effects of air pollution by age groups (Chen et al. (2013); Deryugina et al. (2016)). These results suggest that the bias caused by the measurement error in our imperfect net outmigration measures should be minimal and statistically undetectable.

Table 1 reports mean and standard deviation of our two net outmigration ratio measures. The difference between the adjusted and unadjusted measures coincides with our approximate measure of deaths. The mean five-year death rate in our period is 1.28 percent, also reported in Table 1. On average, the net outmigration ratio is negative (both adjusted and unadjusted). As this ratio is expressed as an average of unweighted percentages at the county level, the mean net outmigration can be either positive or negative. The negative sign likely means that less populated counties, which are also more numerous, are predominantly experiencing net inflows. This could be due to the urbanization policy and the economic development of several economic zones such as the Yangtze River and Pearl River Deltas. The large standard deviation of the net outmigration ratio shows that there is substantial heterogeneity in migration flows across counties. This is also clear from Panel A of Figure 4, which depicts the histogram of the net outmigration ratio with death adjustment. Although average net changes in population are modest, five percent of counties may experience increases of 40 percent in population stemming from migration flows (negative tail of the net outmigration ratio histogram). Large reductions in population due to migration are more rare.

Our second measurement on migration is destination-based immigrants whose hukou are in their origins, or floating migration. This excludes those immigrants who also transfer their hukou to the destination (registered migration). From previous work on Chinese migration (Ebenstein and Zhao, 2015) and from our calculations, we know that about 70 percent of migrants constitute floating migrants.[10] Since the majority of migrants do not transfer their hukou, our destination based immigration captures the bulk of the response to air pollution. Our destination-based immigration measure is calculated from individual-level census in 2000 and 2005, and county-level aggregated census in 2010. The details are available in the online appendix. We cannot calculate origin-based outmigrants because the aggregated data in 2010 only report the destination-based immigrants. As we can see from Table 1, we can also observe an increasing trend in destination-based floating immigration during the period of our study.

3.2.2 Air Pollution

The data on air pollution are derived from the satellite-based AOD retrievals. This technique is particularly popular for estimating air pollutants in areas lacking ground-level measurements (Van Donkelaar et al., 2010). AOD essentially measures the amount of sunshine

[10] Our calculation comes from the 2000 Census, which has information on both floating and registered migration.

duration that are absorbed, reflected, and scattered by the particulates suspended in the air, and can be used to estimate particular matter concentrations. The AOD-based pollution data closely match the ground-based monitoring station measures (Gupta et al., 2006; Kumar et al., 2011).

We obtain the AOD data from the product M2TMNXAER version 5.12.4 from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the National Aeronautics and Space Administration (NASA) of the U.S.[11] The data are reported at each 0.5 degree $\times$0.625 degree (around 50 km$\times$60 km) latitude by longitude grid in each month since 1980. The concentration of SO_2 is reported in the data, while the concentration of $PM_{2.5}$ is calculated following Buchard et al. (2016). The monthly pollution data are then aggregated from grid to county. We then average to annual level across all months and further average to each 5-year period for each county.

We do not use the air pollution data from ground-based monitoring stations for four reasons. First, the publicly available data which are provided by the China National Environmental Monitoring Center (CNEMC) of the Ministry of Environmental Protection of China were only reported starting from June of 2000, while our study period starts from 1996. Second, the spatial coverage is quite sparse. It only covers 42 cities in 2000 and 113 cities in 2010, while AOD-based data cover the whole country and we convert to 2,816 counties. Third, the ground-based pollution data only report Air Pollution Index (API), which is a piece-wise linear transformations of three air pollutants (PM_{10}, SO_2, and NO_2), and thus we cannot explore the effect of specific air pollutant, especially $PM_{2.5}$. Lastly, it is found that ground-based air pollution data have been manipulated (Ghanem and Zhang, 2014).

Though previous studies have shown that AOD-based pollution data can predict air quality (Gupta et al., 2006; Kumar et al., 2011), we still compare our AOD-based data with ground-based data during the period 2013-2015, when CNEMC and US Embassy started to report hourly concentration for the six major air pollutants: $PM_{2.5}$, PM_{10}, SO_2, O_3, NO_2

[11]The data can be downloaded at https://disc.gsfc.nasa.gov/uui/datasets/M2TMNXAER_V5.12.4/summary?keywords=Aerosols#.

and CO.[12] We find no statistical difference between them. The details are discussed in the online appendix.

Table 1 shows descriptive statistics for $PM_{2.5}$ and SO_2. The average concentration of $PM_{2.5}$ during 1996-2010 is 53.27 µg/m^3, which is 6 times than the U.S. EPA's standard. The average concentration of SO_2 during the same period is 15.50 µg/m^3, which is also significantly higher than most countries.

3.2.3 Thermal Inversions

The data on thermal inversions are also from the MERRA-2. In particular, we utilize the product M2I6NPANA version 5.12.4, which divides the earth by 0.5 degree×0.625 degree (around 50 km×60 km) grid, and records the 6-hour air temperature at 42 layers, ranging from surface to 36,000 meters.[13] We aggregate all data from grid to county. Within each 6-hour period, we calculate the temperature difference using temperature in the second layer (320 meters) minus temperature in the first layers (110 meters). If the difference is positive, there exists an thermal inversion and the difference measures the inversion strength. If the difference is negative, it is normal condition and we truncate the difference to zero. We then average the inversion strength across all 6-hour lapses within each 5-year period. We also check the robustness using temperatures in the first and third layers (540 meters) and the results are robust.

Table 1 shows the means and standard deviations for thermal inversion strength as well as the frequency of thermal inversions any 6-hour interval over each of our 5-year periods. The average strength of it during our whole period of study is 0.22°C. During 1996-2010, average thermal inversion strength appears to be increasing at a very slow pace in average. The frequency of thermal inversions also appears to have a very slight increase over the 15

[12] For real-time air pollution and the geographic locations of the eight monitoring stations, please see http://www.cnemc.cn/ from CNEMC and http://www.stateair.net/web/historical/1/1.html from US Embassy.

[13] The data can be downloaded at https://disc.sci.gsfc.nasa.gov/uui/datasets/M2I6NPANA_V5.12.4/summary?keywords=%22MERRA-2%22%20M2I6NPANA&start=1920-01-01&end=2017-01-16.

year period of our study.

3.2.4 Weather

The weather data are obtained from the China Meteorological Data Sharing Service System (CMDSSS), which records daily minimum, maximum, and average temperatures, precipitation, sunshine duration, relative humidity, and wind speed for 820 weather stations in China.[14] We then average temperature, relative humidity, and wind speed, and aggregate precipitation and sunshine duration across days within each year and further average to each 5-year period. We also construct the number of days within each 1°C temperature bin and aggregate over five-year periods.

4 Results

4.1 First-stage Results: The Effect of Thermal Inversion on Air Pollution

Table 2 presents the first-stage estimates of the effect of thermal inversions on air pollution conditional on county and period fixed effects. Dependent variables are concentrations of $PM_{2.5}$ in Panel A and SO_2 in Panel B. All regressions control for county and period fixed effects as well as weather controls, including temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine duration. Column (2) shows the results without population weights, while column (3) uses population aged 15 to 60 in 1995 in column (3).

We find significant and robust effects of thermal inversions on both air pollutants. As the measure of thermal inversion strength is somewhat difficult to interpret in terms of magnitude, one can multiply the point estimates in Panel A by 0.004 (0.22/53.08) and by

[14]CMDSSS was developed and is currently managed by the Climatic Data Center, National Meteorological Information Center, China Meteorological Administration. See http://data.cma.cn/ for details.

0.014 (0.22/15.39) in Panel B in order to convert to elasticities. The point estimates in column (1) suggest that a 1 percent increase in average thermal inversion strength leads to a 0.3 percent increase in $PM_{2.5}$ concentrations. We find a similar elasticity in the case of SO_2. Weighting by population, shown in column (2), yields similar results. Table 2 also reports the Kleibergen-Paap (KP) F-statistics, and all of them are well above Stock and Yogo's 10% maximal bias threshold.[15]

4.2 Second-stage Results: The Effect of Air Pollution on Migration

Table 3 reports the estimates of air pollution on the net outmigration ratio with and without adjusting for approximate deaths. Recall that Section 3.2 and Appendix Tables A.10 and A.11 show that among the population we focus on, those between 15 and 60 years of age, there are no effects of pollution on deaths. Thus, failing to subtract deaths from the outmigration ratio should not affect our estimates. Nevertheless, in columns (4) to (6) we show results that adjust for approximate deaths, which are calculated based on deaths in the last year of each period.

Columns (1) and (4) report the OLS estimates of equation (1), while columns (2)-(3) and (5)-(6) report the IV estimates with and without population weights. All regressions include county and period fixed effects. Panels A and B show the effects of $PM_{2.5}$ and SO_2 respectively. Note that these effects come from separate regressions. Thus, adding them would result in double-counting, as the concentrations of these two pollutants are correlated. Instead, the right way to interpret them is as the effects on net outmigration stemming from two different ways of measuring air pollution.[16]

We first discuss the results of air pollution on net-outmigration ratios without adjusting

[15]We have also tried using the yearly count of thermal inversions as an instrument as well as the number of extreme thermal inversions. However, the average strength measure yields the highest KP F-statistics.

[16]To address double counting, we look at two pollutant and pollution index models in Table 8, which we discuss below.

for deaths. The OLS estimates in column (1) in both Panels suggest a positive and significant correlation between air pollution and net outmigration after controlling for weather variables as well as county and period fixed effects. Note that pollution is endogenous in this specification and may be correlated with other determinants of migration that vary over time within counties —such as wage, GDP, job opportunities, and infrastructure —which would result in omitted-variable bias. As many of these potentially omitted factors are likely to attract migrants, the omitted-variable bias is likely negative. The OLS estimates may also be biased downwards due to reverse causality, as positive net-outmigration flows may bring down pollution.

Consistent with the expected bias discussed above, IV estimates of the effect of air pollution on net outmigration ratios are larger in magnitude. Columns (2) and (3) show IV estimates of equation (1), in which pollution is instrumented with the average strength of thermal inversions. Our preferred specification is equation (3), which controls includes population weighting. Column (3) shows an effect of pollution on outmigration flows that is nearly twice the size of the OLS effect.

The magnitude of the effect of air pollution, whether it is measured by $PM_{2.5}$ and SO_2, on net outmigration flows is large and economically significant. First, we note that the semi-elasticity is similar across the two pollutants: $PM_{2.5}$ and SO_2. A ten percent increase in $PM_{2.5}$ induces a reduction in population of 2.7 per 100 inhabitants due to migration. Similarly, when we measure pollution using SO_2 concentrations, we find that a ten percent increase in SO_2 induces a reduction in population of 2.3 per 100 inhabitants due to migration. Second, we note that this effect is economically meaningful when we consider the magnitude of the changes in air pollution that China has experienced in the last 15 years. In order to apply our estimates to observed changes in air pollution in China, is important to understand that the type of variation we use for identification corresponds to relative changes in air pollution as we control for period fixed effects. Hence, although Figure 2 shows that air pollution levels increased by more than 60 percent average (27 $\mu g/m^3$), the variation in air pollution that our estimates can be applied to is closest to what is presented in Figure 3. Here we can see that there was wide heterogeneity in air pollution changes over our period of study, and that over this period there are several counties that experienced changes larger than 40 $\mu g/m^3$(a 48 percent increase relative to the national average) and smaller than 10 $\mu g/m^3$(a 63 percent reduction relative to the national average). Thus, assuming linearity, our estimates imply that these counties experienced changes in population between 11.04 (0.23×48) and 17.01 (0.27×63) per 100 inhabitants due to pollution-spurred migration. These effects are large, but in line with observed changes in population due to migration: the standard deviation of net outmigration flows is 16.15 per 100 (shown in Table 1).

Column (2) of Table 3 shows the same specification without population weighting. Weighting is potentially important in our setting for two reasons. First, when we weight by population, we account for the fact that our dependent variable is more precisely estimated in counties where population is large. Second, they provide a different weighted average of local effects that better reflects the flows faced by a representative individual rather than a representative county. Responses could be different in more populated areas if these areas tend to be wealthier, more educated and/or there are non-linearities in the dose-response function (as these areas tend to be more polluted). Two observations emerge from these comparing our unweighted results to column (3). The first one is that the size of the standard error is not very different, suggesting that inference in unweighed regressions is not misleading. The second one is that the effect of $PM_{2.5}$ and SO_2 on net outmigration are similar whether or not we weigh by population. The similarity of point estimates in between columns (2) and (3) suggest that underlying heterogeneity across regions in terms of population is not very important. Nevertheless, we explore other dimensions of heterogeneity in our estimates in Table 5.

Finally, Columns (4)-(6) show our estimates when we adjust the dependent variable for deaths by using deaths observed in the last year of each period multiplied by five. Results change very little compared to columns (1)-(3).

Next, we discuss the results concerning our destination based immigration measure. There are two important differences in the interpretation of these results with respect to the previous discussion. First, destination based immigration corresponds to floating immigration only. This means that formal immigration, which is more costly (Kinnan, Wang, and Wang, 2016), is excluded from this measure (see Section 3.2.1). Second, our dependent variable is a measure of immigration as opposed to (net) outmigration. This has a couple of important implications. First, if individuals value air quality, then we will expect air pollution to have a negative effect on immigration flows (the opposite sign to the effect of pollution in Table 3). Second, finding a response of immigration flows to air pollution relies on more demanding assumptions about people's economic behavior. In contrast with measures of outmigration which capture the effect of changes in the amenity where people live, immigration measures capture the effect of changes in the amenity where people move to. Thus, for us to capture the effects of air pollution using this measure, individuals need to be aware of pollution changes in the where they are planning to move to as opposed to pollution changes in the county where they live. Nevertheless, we find results that are consistent with people moving to counties whose pollution has improved due to fluctuations in thermal inversions.

Table 4 reports the estimates of pollution on destination based immigration. The structure of the table is the same as that of Table 3, columns (1)-(3). The OLS estimates in column (1) suggest a significantly positive relationship between air pollution and immigration (the opposite sign to what one would expect from the causal relationship). As in column (1) of Table 3, pollution is endogenous in this specification. The omitted variable bias in this case is likely to bias our coefficient of interest upwards, as pollution is correlated with economic activity. In the case of immigration, the bias seems to be large enough to flip the sign of the expected causal relationship. When we instrument air pollution using strength of thermal inversions, we find significantly negative effects of air pollution on immigration. Our preferred estimates in column (3) imply that a 10 percent reduction in $PM_{2.5}$ brings in 1.7

people per 100 inhabitants, while a reduction of 10 in SO_2 results in a gain of 1.4 immigrants. The smaller magnitude of the effects compared to net-outmigration ratios is to be expected as net-outmigration would capture the effect of air pollution on both inflows and outflows; while immigration only captures the effect on inflows. In addition, official migration (which is not captured by this measure) is less than one third of overall migration according to our calculations from the 2000 census (see Section 3.2.1 and Ebenstein and Zhao (2015)).

Column (2) of Table 4 omits the population weights from the estimation. In the case of destination based immigration, population weights seem to matter more for the magnitude of the effect: the immigration effects faced by the average person in China seem to be slightly larger than those faced by the average county.

4.3 Additional Evidence

In the previous section, we find a robust and significant effect of air pollution on migration for adult population. In particular, high pollution induces people to leave, and low pollution induces people to arrive. Below we further explore the heterogeneity of these impacts.

4.3.1 By Education

Our first focus is education, since education is an important determinant of income and is likely fixed for most of the adults in our sample. In addition, highly educated population may be more sensitive to air pollution because, on the one hand, they have better knowledge in understanding the harmful effects of air pollution on human body, and on the other hand, they have the ability to change their registration. If this is the case, we should expect a larger effect of air pollution on net outmigration for highly educated population.

Table 5 presents the IV estimates of air pollution on net outmigration ratio for three categories of education level in columns (1)-(3): junior high school or below, high school, and college or above.[17] All models include county and period fixed effects, flexible weather

[17] The data on destination based immigration by education level are not available.

controls and are weighted by population. We use inversion strength to instrument $PM_{2.5}$ in Panel A and SO_2 in Panel B.

We find positive and significant effects of $PM_{2.5}$ on net outmigration for all educational categories. In addition, the marginal effects are monotonically increasing in the level of education. For example, the estimated coefficient of $PM_{2.5}$ for adults with college degree or above is twice the size of the effect for population with junior high school education or below. The effects are qualitatively similar if we use SO_2 as our endogenous measure of air pollution. These findings confirm our hypothesis that highly educated population are more likely to migrate to other counties in response to increased air pollution. Importantly, these findings suggest that air pollution may have important effects on labor force and socioeconomic composition. Air pollution may impose significant economic costs on local regions and cause the so called "brain drain effect" (Fischer, 2003). In addition, our findings support other recent literature that has found effects of air pollution on the socioeconomic composition of neighborhoods (Hanlon, 2016; Heblich, Trew, and Yanos, 2016).

4.3.2 By Gender and Age Cohort

We next focus on heterogeneity by gender and age cohort. Table 6 presents the IV estimates of air pollution on net outmigration ratio for males in column (1) and females in column (2). In column (3), we focus on population aged 15-30, while in columns (4) and (5), we focus on population aged 30-45 and 45-60, respectively. All models include county and period fixed effects and weather controls. Average strength of thermal inversions is used as IV.

We find positive effects of pollution on net outmigration for both genders, although the effect for males is marginally significant. The effects for females are almost twice as high as for males, which suggests that a potential pattern of migration where the head of the household may stay behind while the rest of the family migrates to a cleaner location. In terms of age cohort, we find that the effects are the largest for younger cohorts and monotonically decreases with age, indicating that this group might be more sensitive to air pollution (perhaps because they have young children) and/or have higher ability to move.

One additional thing to note is that the potential upwards bias induced by our inability to properly controlling for death counts would be strongest for the oldest group (column (5)). The fact that this group shows the smallest effect reinforces our assessment that the response of deaths to air pollution is not significantly biasing our estimates.

4.3.3 By Origins of Immigration

The data on destination based immigration not only report the number of immigrants, but also report the origins of those immigrants in three categories: from other counties within the same province, from other provinces, and within counties. As the source of air pollution variation is unlikely to induce within-county differences in air pollution, we should not expect migration flows within counties unless our instrument is capturing some other determinant of migration. Thus, this detail of the data allow us to (a) inquire whether most of the floating migration flows occur within provinces or outside provinces and (b) conduct a robustness check on our research design and instrument validity. Table 7 reports our results on destination based immigration by each type of flow. We find significantly negative effects of pollution on destination based immigration for both movements across counties within a province and movements across provinces (Columns (2) and (3)). However, migration within a province appears to be twice as large as migration across provinces. This is unsurprising given our earlier observation on the gender imbalance, which suggests that heads of household may be staying behind. If this were the case, remaining within the same province might be less costly for the family. It is also possible that families may be able to change their residence without changing their job when remaining within the same province. These results suggest that immigrants might be trying to minimize pollution exposure, while at the same time remaining within the same region where costs of migrating are smaller.

Column (4) shows the response of destination-based immigration within counties to air pollution. The effect is very close to zero in magnitude and non significant, lending support to the notion that our instrument is unlikely to have effects on other determinants of migration.

4.4 Multiple pollutant models

In all the IV specifications above, we run regressions models separately for $PM_{2.5}$ and SO_2. Therefore, the estimated coefficient captures the effect the specified pollutant along with the effect of any other pollutants that are correlated with it and respond to thermal inversions. To explore the separate effects of the two pollutants we have data for, we use two approaches. The first approach is to regress two air pollutants simultaneously in one regression model, and use two IVs: thermal inversion strength and counts. The second approach is to construct a single pollution index, the air quality index (AQI), which is essentially a piece-wise linear transformation of two pollutants.[18] The AQI is particularly interesting, as it would be similar to the pollution measure that is reported by the government, and thus the measure that individuals are likely to respond to. The pollution index is then instrumented by thermal inversion strength.

The results are presented in Table 8, in which migration is measured by net outmigration ratio in columns (1) and (2), and by destination-based immigration in columns (3) and (4). In columns (1) and (3), we include both air pollutants in one regression model. We also report the Sanderson-Windmeijer F-statistics for test of weak instruments for each endogenous variable conditional on the other, as well as the test statistic and p-value for joint significance. In columns (2) and (4), we only include the single pollution index, or the AQI.

When we include both air pollutants in the model, we find non-significant individual effects of pollution on net-outmigration; but a highly significant joint effect of both pollutants (column (1)). Because of the imprecision of the individual coefficients, it is difficult to assess which pollutant is playing the more important role. When we use destination-based immigration as our outcome variable, we find that $PM_{2.5}$ slightly dominates as a one percent

[18] See detailed calculation method in http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/t20120302_224166.htm.

increase in this pollutant results in 0.29 percent increase in population due to floating immigration, while a one percent increase in SO_2 results in a 0.14 increase in population. The joint effect is similarly significant at the 1% level.

When we use AQI to incorporate two pollutants into one single index, we also find statistically significant and comparable effects. During the period 1996-2010, the average five-year AQI increase has been of 11.69 points. This suggests that counties that experienced a five-year change in pollution similar to the country's average saw a 5 percent (0.4269% $\times$ 11.69) drop in the adult population through migration in response to this increase (under the linearity and independence assumptions discussed above). Of this, 3.05 percentage points (-0.2611% $\times$ 11.69) appear to be driven by a slowdown of floating immigration flows (column (4)), assuming symmetry in the effects of air pollution. Note that our effects aim at isolating the causal effect of pollution forces on migration. Total observed migration flows over this period that are substantially different to these calculations are perfectly consistent with these estimates, as migration flows are a function of many other variables besides air pollution. Nevertheless, note that large five-year changes in population due to migration are not rare (see Figure 4).

4.5 Robustness Checks

Here we discuss the results of several robustness checks to the main results in Tables 3 and 4. The results of these robustness checks are presented in Table 9. We start by clustering standard errors at different levels. In the baseline, standard errors are clustered at county level, which accounts for autocorrelation of the error terms over periods within each county. In column (2), we cluster standard errors at prefecture level, an administrative level in China which usually includes 10-20 counties, to account for both autocorrelation and spatial correlation across counties within each prefecture. Though standard errors are about twice as large, the effects are still statistically significant at the 5% level for both pollutants. The KP F-statistic for weak instruments is quite lower, but still above the Stock-Yogo critical value for 10% relative bias.[19]

In the baseline, we use period fixed effects to control for common shocks for the whole country in each period, such as global economic trend and national policies. In column (3), we replace period fixed effects with period-by-province fixed effects, to control for common shocks within each province. This specification shows that our results are robust under a more stringent identification assumption that allows for province-specific trends in unobserved determinants of migration trends to coincide with thermal inversion patterns over time. In column (4) we replace the baseline weights (1995 population) with average population during the 1996-2010 period. Results are very similar to our baseline.

Columns (5) and (6) check the robustness of our results to different instrumental variables. In column (5) we test the robustness of using different layers of temperature to calculate thermal inversion. Our baseline model uses temperatures in the first and second layers (110 and 320 meters). Column (5) shows the results with temperatures in the first and third layers (110 and 540 meters). Our results are robust alternative layers of inversion. In column (6) we use number of days with thermal inversion as our instrumental variable instead of inversion strength. Our results are robust to this alternative definition as well.

Finally, column (7) probes the robustness of our results to alternative weather controls. The temperature controls used in the baseline are quite flexible, as they allow for temperature in each degree bin to have a different effect on migration. However, this specification does not allow for heterogeneity of these effects across regions. As Figure A.7 demonstrates, the relationship between weather and inversions is different for different regions. If for any reason there was a spurious correlation pattern of temperature and migration that coincided with this heterogeneity, temperature could still bias our results. Thus, column (7) includes interactions between all of our standard weather controls and six region dummies. Results are very similar to our baseline results, which rules out that differential temperature-migration

[19] We also experiment with two-way clustering at prefecture and period level to account for potential spatial correlation and nation-wide weather patterns that could result in similar deviations from the mean occurrence in thermal inversions. Our effects (not reported) are also robust to this specification of the variance matrix.

patters across regions are being picked up by our instrument.

5 Discussion and Conclusions

Our findings suggest that population in China are willing to forgo potentially very large costs and hurdles to protect themselves from air pollution. To put our estimates into perspective, Kinnan, Wang, and Wang (2016) find that each province-level reform of the hukou system resulted in a 32 percent increase in the migration inflow. Our estimates suggest that, had a single county experienced a five-year increase in air pollution similar to the country's average (everything else equal), this county would have seen a reduction of 3 percent of its population due to reduced floating migration, which represents a drop of 50 percent in the average migration inflow. We also find that had a single county experienced a five-year increase in air pollution similar to the country's average increase, this county would have lost about 5 of its population due to pollution-induced migration. Note that in the interpretation of our estimates we emphasize a change in pollution in a single county. This is due to the nature of our instrument: it captures abnormally high pollution due to a local and temporary burst in the strength and/or frequency of thermal inversions. This limits the risk of capturing general equilibrium effects, as the outmigration component of the net-flow would have been unlikely to change housing prices and wages in receptor counties. The fall in inflows, however, could have affected local prices in the short-run. A drop in local housing prices (and an increase in local wages) would have tempered the partial equilibrium effect, leading to a smaller response to air pollution.

The actual changes in pollution that occurred between 1996 and 2010 might have had different effects on migration to the ones we identify in this paper for two reasons. First, although pollution increased at different rates in different regions (see Figure 3), these changes were highly correlated across counties between 2000 and 2010 due to the acceleration of manufacturing activity throughout the country. Correlated changes would have resulted in much stronger impacts on house prices and wages than uncorrelated changes in air pollution (i.e. rural areas would have felt the inflow pressure from many affected counties). Second, the long-run effect might be different if house stocks take some time to adjust. Our estimates correspond to a five-year change in air pollution, which may allow for little adjustment in the house stock. If the effect of the inflow slow-down is large enough to bring down house prices, then our estimates of the inflow response could carry a house price reduction effect. 10-year or 15-year effects of permanent changes in air pollution may lead to different house price effects as house stocks would have had more time to adjust.

Although at this point it is hard to use our estimates to put a value number on the cost of these relocation decisions, which would be helpful to draw conclusions about the willingness to pay for air pollution reductions, we use the returns to migration in Kinnan, Wang, and Wang (2016) to at least provide some idea about the order of magnitude of the cost of migrating. Kinnan, Wang, and Wang (2016) find that households that migrate in response to a hukou reform increase income by 1.2 percent.[20] If we assume that the benefits of migrating are constant (which is admittedly a strong assumption), then the marginal migrant would be facing a cost of migrating that is at least as high.

Our results so far do shed light on a number of interesting questions. First, we show that individuals do incorporate air pollution information on counties of origin and destination into their migration decisions and that they pay attention to changes in air pollution over several years. Second, along with recent literature, we provide evidence that pollution is yet another force that reshapes the sociodemographic distribution of locations and labor force as highly educated people are more likely to respond to changes in air pollution. Third, we show that the effects appear to be different by age and stronger for individuals at the beginning of their professional careers. This is particularly interesting, as so far the estimates of the cost of air pollution in terms of a loss of health and/or life have been shown to be concentrated among elderly and very young individuals. Our paper suggests that individuals in working

[20] The yearly income per capita is of 774 USD.

age might be willing to forgo earnings in response to air pollution, facing a pecuniary cost rather than health related costs.

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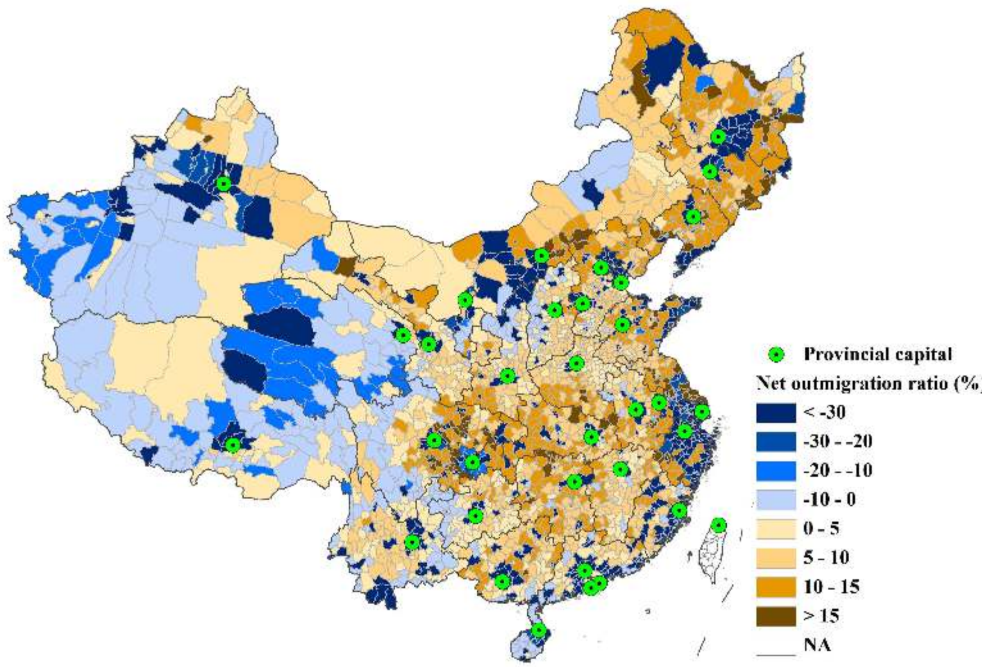
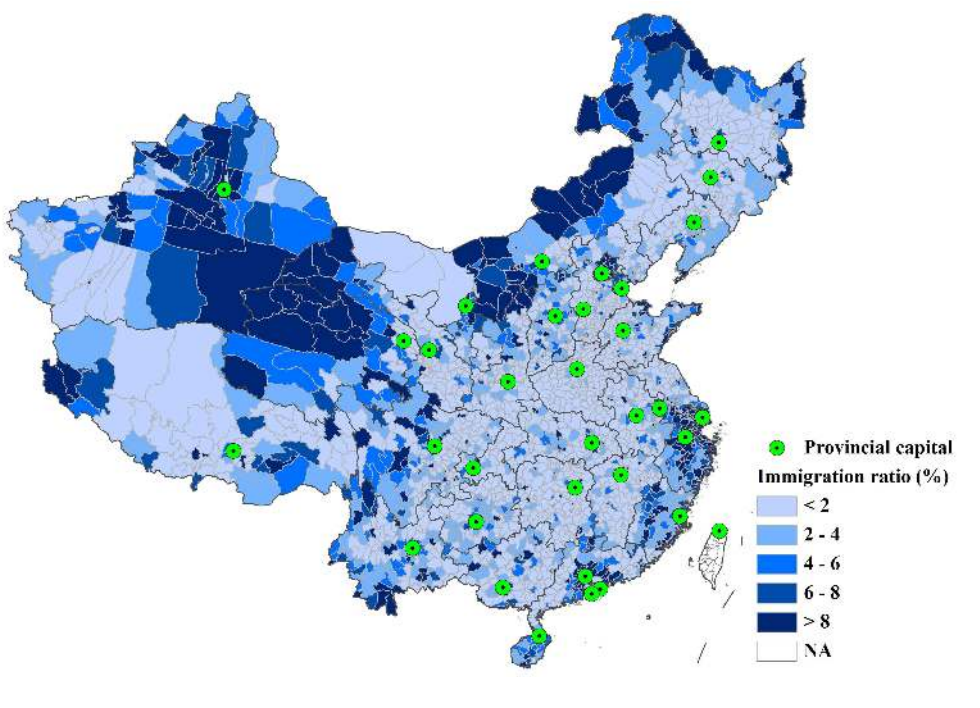
Figure 1: Migration in China (1996-2010)

Panel A: Net Outmigration Ratio



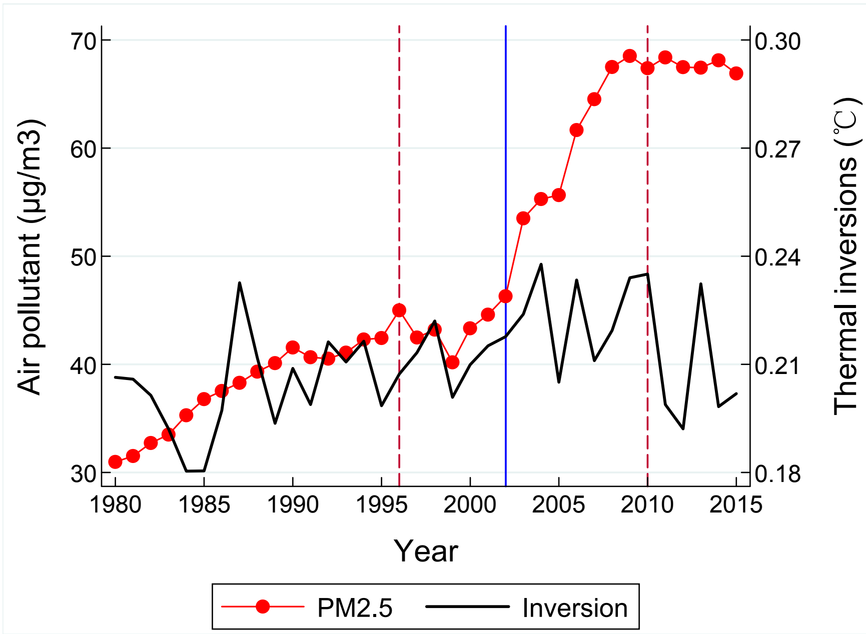
Panel B: Destination-based Immigration Ratio



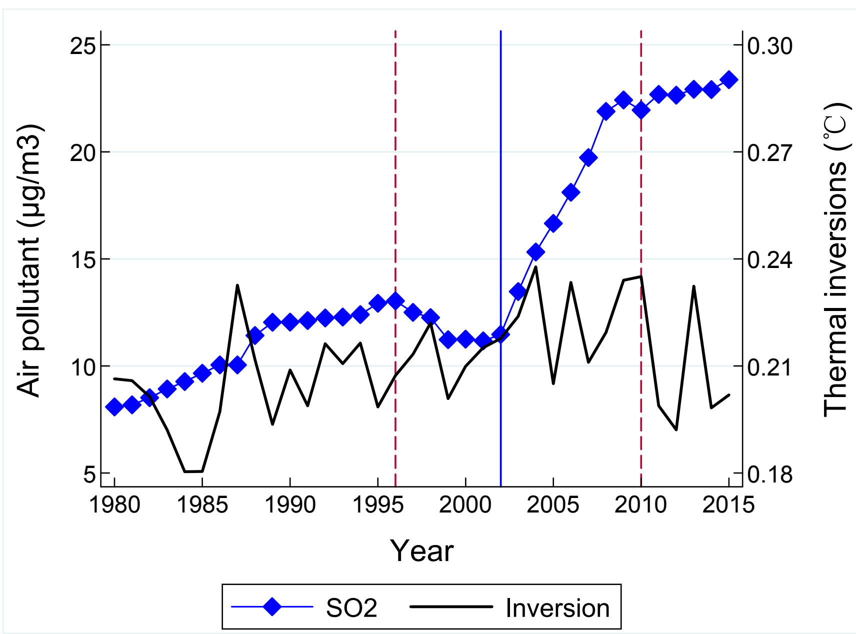
Notes: This figure depicts the average migration for each county in China over the period 1996-2010. In Panel A, migration is measured by net outmigration ratio, which is the percent of population leaving the county net of new arrivals and deaths. In Panel B, migration is measured by destination-based immigration ratio, which is defined as the percent of population entering the county with their hukou in the origin.

Figure 2: Time Trend of Air Pollution and Thermal Inversion in China (1980-2015)

Panel A: $PM_{2.5}$ and Thermal Inversion



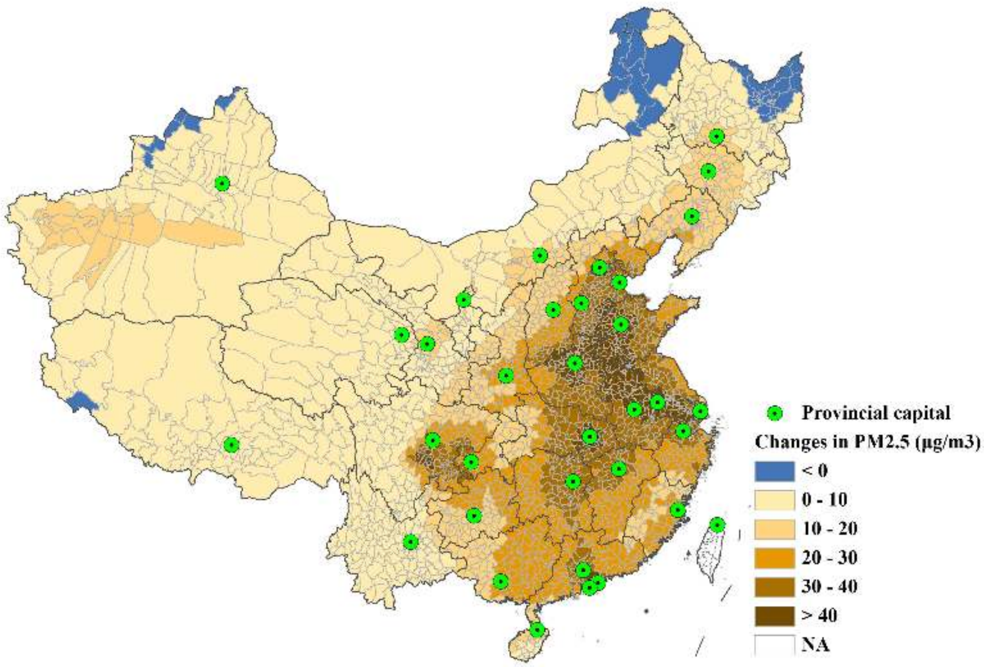
Panel B: $SO_{2.5}$ and Thermal Inversion



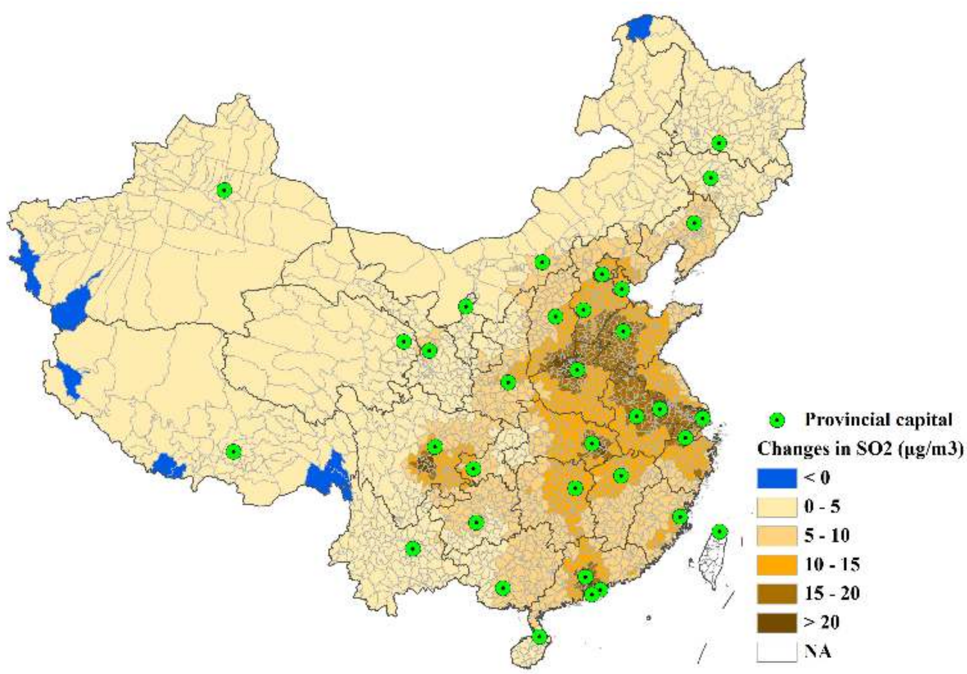
Notes: This figure plots the county-average concentration of $PM_{2.5}$ and thermal inversion (panel A) and SO_2 and thermal inversion (panel B) in each year in China over the period 1980-2015. Two red vertical lines highlight the course of our study: 1996-2010. The blue vertical line highlights the year of 2001, when China joined the WTO and pollution has been significantly increased.

Figure 3: Pollution Changes in China (1996-2010)

Panel A: $PM_{2.5}$



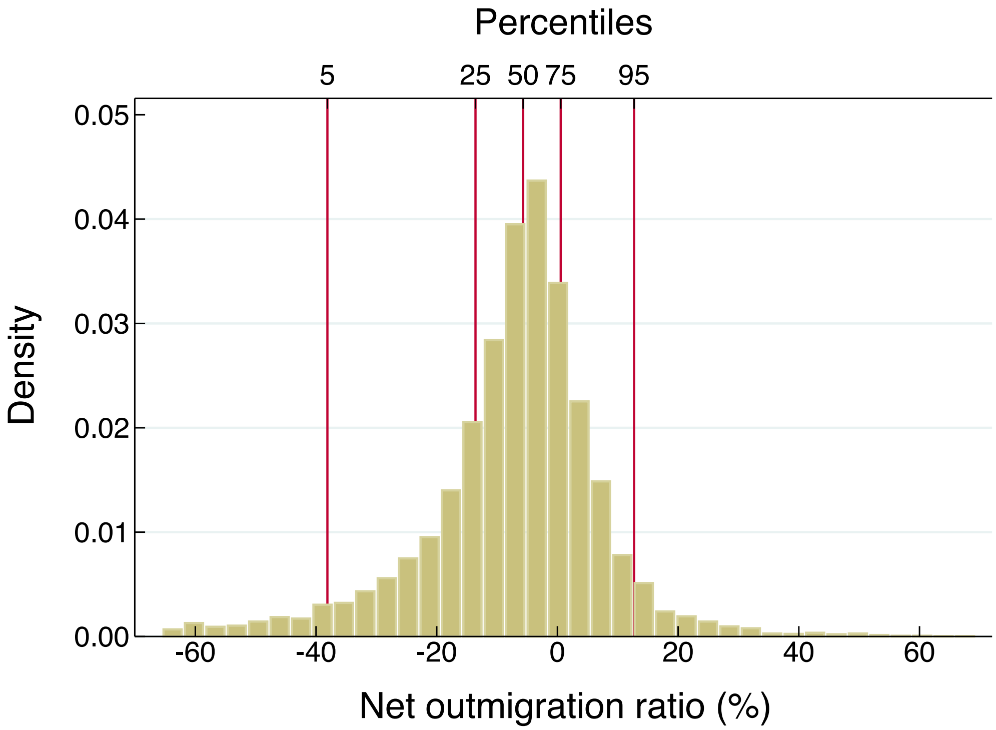
Panel B: SO_2



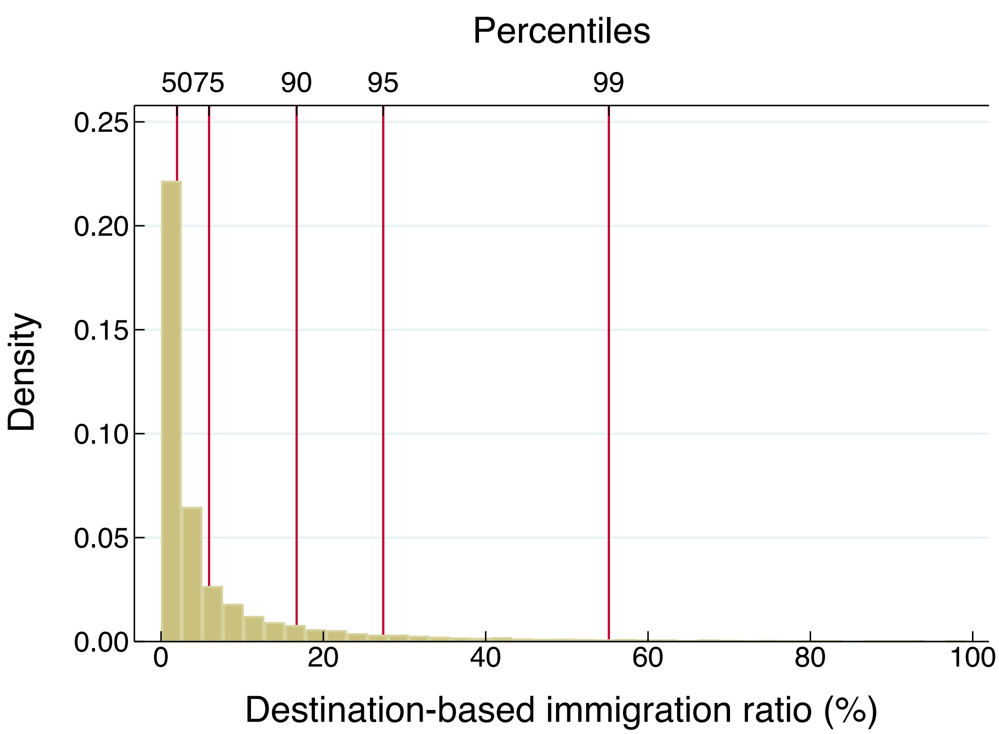
Notes: This figure depicts the changes in $PM_{2.5}$ (panel A) and SO_2 (panel B) between the period 1996-2000 and 2005-2010 for each county in China.

Figure 4: Histogram of Net Outmigration Ratio and Destination-based Immigration Ratio

Panel A: Net Outmigration Ratio with Death Adjustment

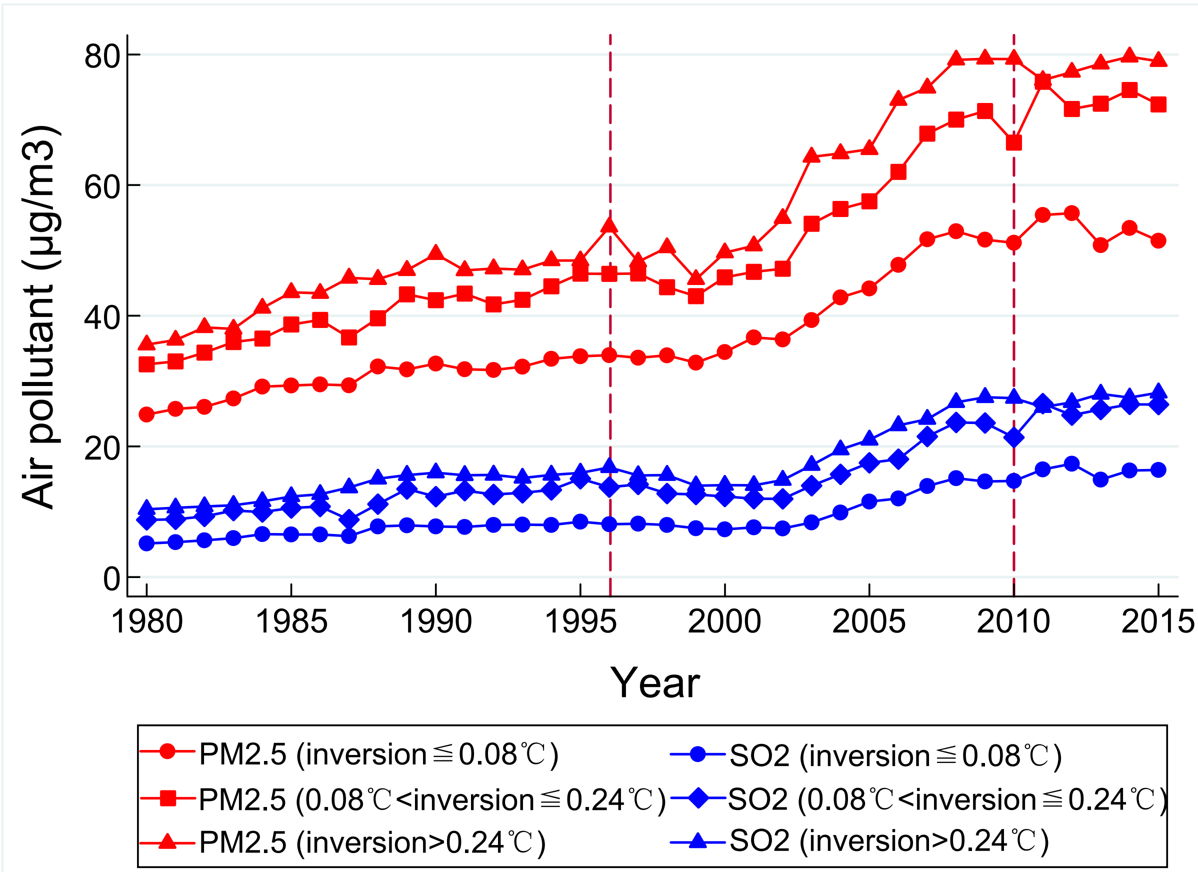


Panel B: Destination-based Immigration Ratio



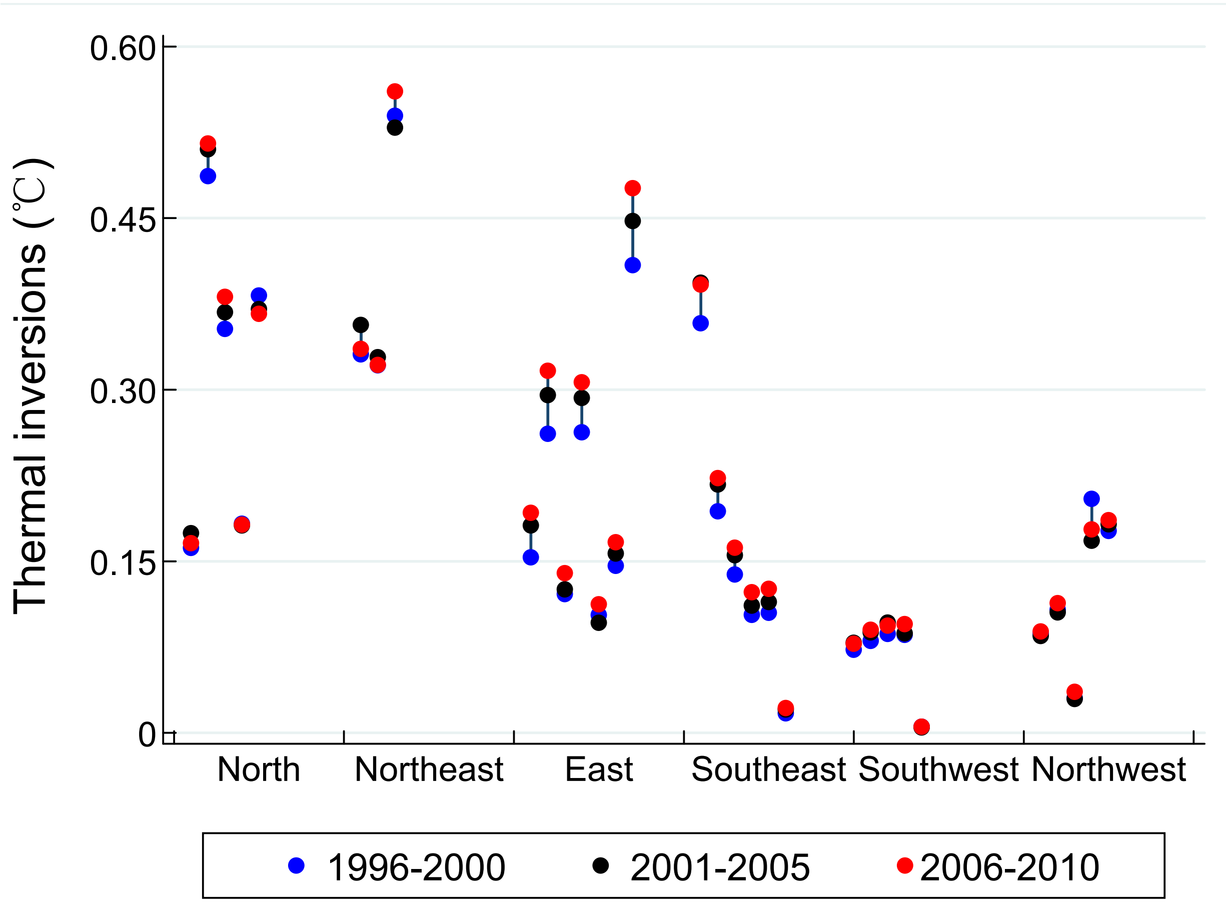
Notes: This figure plots the histogram of net outmigration ratio with death adjustment (panel A) and destination-based immigration ratio (panel B). Percentiles 5, 25, 50, 75, and 95 are highlighted in red.

Figure 5: Time Trend of Air Pollution by Occurrences of Thermal Inversion (1980-2015)



Notes: This figure plots the county-average pollution concentration in each year over the period 1980-2015 for three categories: thermal inversion strength less than 0.08 °C (33th percentile), between 0.08 and 0.24 °C (66th percentile), and above 0.24 °C. Two red vertical lines highlight the course of our study: 1996-2010.

Figure 6: Five-year Average of Thermal Inversion Within Each Province



Notes: This figure depicts the five-year average of thermal inversion strength for three periods –1996-2000, 2001-2005, and 2006-2010 –within each province.

Table 1: Summary Statistics

		1996-2010		1996-2000		2001-2005		2006-2010	
Variable	Unit	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Migration									
Net outmigration ratio (death adjustment)	%	-9.17	16.15	-6.61	9.89	-5.82	16.39	-15.08	19.07
Net outmigration ratio (no death adjustment)	%	-7.89	16.04	-5.30	9.83	-4.46	16.25	-13.90	18.88
Destination-based immigration ratio	%	6.01	10.73	3.41	6.16	4.20	7.49	10.40	14.90
Destination-based immigration ratio by origin									
Within county	%	4.45	4.53	2.50	2.23	3.02	3.48	7.84	5.20
Across county within province	%	3.66	6.72	2.37	4.10	2.36	4.16	6.25	9.56
Across county outside province	%	2.58	5.93	1.72	4.06	1.88	4.71	4.15	7.94
Death rates	%	1.28	0.54	1.31	0.39	1.35	0.61	1.19	0.57
Air pollution									
$PM_{2.5}$	$\mu g/m^3$	53.08	27.93	42.68	19.85	50.89	24.53	65.67	32.76
SO_2	$\mu g/m^3$	15.39	11.90	11.97	8.90	13.52	9.74	20.67	14.41
Thermal inversion									
Strength	°C	0.22	0.19	0.21	0.19	0.22	0.20	0.23	0.20
Probability of occurrence	%	16.39	9.81	16.07	9.65	16.47	9.95	16.64	9.83

Notes: The unit of observation is county-period (5-year). Number of observations is 7,911. Net outmigration ratio is defined as the percent of population (aged 15 to 60) leaving the county net of new arrivals and deaths. Destination-based immigration ratio is defined as the percent of population (aged 15 to 60) entering the county with their hukou in the origin. Death rates are for population (aged 15 to 60). Pollution data are reported at monthly level, and then are averaged to each year and further to each period. Thermal inversion strength is calculated using the temperature difference in altitudes of 110 and 330 meters within each 6-hour period, and then is averaged for each five-year period. Positive difference indicates an existence of a thermal inversion with magnitude representing the strength, while negative difference indicates an non-existence of a thermal inversion and is truncated to zero. The probability of occurrence is the averaged dummy variables for each 6-hour period with 1 indicating the existence of a thermal inversion, i.e., temperature in the layer of 110 meters is lower than that in the layer of 330 meters, and 0 otherwise.

Table 2: The Effect of Thermal Inversions on Pollution (First Stage)

	(1)	(2)
Panel A: $PM_{2.5}$		
Thermal inversions	78.6938***	82.0176***
	(5.4654)	(5.1621)
KP F-statistics	206.3	250.9
Panel B: SO_2		
Thermal inversions	24.9499***	28.2183***
	(2.3596)	(2.4171)
KP F-statistics	111.2	135.4
Observations	7,911	7,911
County FE	Yes	Yes
Period FE	Yes	Yes
Weather controls	Yes	Yes
Weighting	No	Yes

Notes: Dependent variables are $PM_{2.5}$ in Panel A and SO_2 in Panel B. Regression models are estimated using Equation (2) and include county fixed effects and period fixed effects. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population aged 15 to 60 in 1995 in column (3). Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table 3: The Effect of Pollution on Net Outmigration Ratio

	No death adjustment			Death adjustment		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
$PM_{2.5}$	0.2898***	0.5786***	0.5156***	0.2967***	0.5934***	0.5309***
	(0.0584)	(0.1637)	(0.1743)	(0.0589)	(0.1656)	(0.1762)
KP F-statistics		206.3	250.9		206.3	250.9
Panel B						
SO_2	0.8243***	1.8251***	1.4989***	0.8439***	1.8716***	1.5433***
	(0.1204)	(0.5265)	(0.5069)	(0.1213)	(0.5329)	(0.5123)
KP F-statistics		111.2	135.4		111.2	135.4
Observations	7,911	7,911	7,911	7,911	7,911	7,911
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Weighting	Yes	No	Yes	Yes	No	Yes

Notes: The dependent variable is net outmigration ratio. Through columns (1)-(4), net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals, without death adjustment. Through columns (5)-(9), net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and death. Regression models are estimated using Equation (1) and include county fixed effects and period fixed effects. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population aged 15 to 60 in 1995 in columns (1), (4), and (8). Standard errors are listed in parentheses and clustered at county level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: The Effect of Pollution on Destination-based Immigration Ratio

	OLS	IV	
	(1)	(2)	(3)
Panel A			
$PM_{2.5}$	0.1258***	-0.2526***	-0.3247***
	(0.0299)	(0.0679)	(0.0820)
KP F-statistics		206.3	250.9
Panel B			
SO_2	0.3603***	-0.7967***	-0.9439***
	(0.0675)	(0.2215)	(0.2486)
KP F-statistics		111.2	135.4
Observations	7,911	7,911	7,911
County FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Weighting	Yes	No	Yes

Notes: The dependent variable is destination-based immigration ratio, which is defined as the percent of population aged 15 to 60 entering the county with their hukou in the origin. Regression models are estimated using Equation (1) and include county fixed effects and period fixed effects. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population aged 15 to 60 in 1995 in columns (1) and (4). Standard errors are listed in parentheses and clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Effect of Pollution on Net Outmigration Ratio: By Education

	Below Junior high school (1)	High school (2)	College or above (3)
Panel A			
$PM_{2.5}$	0.4723**	0.5736**	0.9314**
	(0.2350)	(0.2427)	(0.4433)
KP F-statistics	300.9	224.2	169.7
Panel B			
SO_2	1.3406**	1.6849**	2.6684**
	(0.6687)	(0.7140)	(1.2705)
KP F-statistics	161.2	118.6	96.25
Observations	7,662	7,673	7,617
County FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Weighting	Yes	Yes	Yes
Share in the population (%)	36.67	40.87	22.46

Notes: The dependent variable is net outmigration ratio by each educational level. Net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and deaths. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population for each educational level in 1995. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table 6: The Effect of Pollution on Net Outmigration Ratio: By Gender and Age Cohort

	Male	Female	Age between 15-30	Age between 30-45	Age between 45-60
	(1)	(2)	(3)	(4)	(5)
Panel A					
$PM_{2.5}$	0.3595*	0.6973***	0.7446**	0.6895***	0.0468
	(0.1935)	(0.1847)	(0.3173)	(0.2089)	(0.2556)
KP F-statistics	250.9	250.9	269.4	255.6	281.1
Panel B					
SO_2	1.0450*	2.0271***	2.1896**	1.9962***	0.1336
	(0.5622)	(0.5380)	(0.9294)	(0.6139)	(0.7289)
KP F-statistics	135.4	135.4	138.1	138.8	149.2
Observations	7,911	7,911	7,911	7,911	7,911
County FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes
Weighting	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is net outmigration ratio by each gender and age cohort. Net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and deaths. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population for each subgroup in 1995. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table 7: The Effect of Air Pollution on Destination-based Immigration Ratio: By Origins

	Total immigration	Across county within province	Across county outside province	Within county
	(1)	(2)	(3)	(4)
Panel A				
$PM_{2.5}$	-0.3247***	-0.1779***	-0.0853**	-0.0090
	(0.0820)	(0.0595)	(0.0409)	(0.0076)
KP F-statistics	250.9	250.9	250.9	250.9
Panel B				
SO_2	-0.9439***	-0.5171***	-0.2479**	-0.0261
	(0.2486)	(0.1771)	(0.1210)	(0.0221)
KP F-statistics	135.4	135.4	135.4	135.4
Observations	7,911	7,911	7,911	7,911
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Weighting	Yes	Yes	Yes	Yes

Notes: The dependent variable is destination-based immigration ratio, which is defined as the percent of population aged 15 to 60 entering the county with their hukou in the origin that is different from the destination county. Column (1) includes all migrants regardless of origins. Column (2) includes migrants whose origins are within the province. Column (3) includes migrants whose origins are outside province. Column (4) includes migrants whose origins are within the same county but in another township. Column (4) serves as a placebo test because we only define migrants across counties. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population aged 15-60 in 1995. Standard errors are listed in parentheses and clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Multiple Pollutant Models

	Net outmigration ratio		Immigration ratio	
	Multiple pollutant models	Single pollutant index	Multiple pollutant models	Single pollutant index
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0416	—	-0.5454*	—
	(0.6418)	—	(0.2809)	—
SO_2	1.7405	—	0.9236	—
	(1.8227)	—	(0.7973)	—
AQI	—	0.4269***	—	-0.2611***
	—	(0.1415)	—	(0.0660)
KP F-statistics	38.13	252.5	38.13	252.5
p-value of joint sig.	0.0003	—	0.0008	—
SW F-statistics for $PM_{2.5}$	104.02	—	104.02	—
SW F-statistics for SO_2	83.51	—	83.51	—
Observations	7,911	7,911	7,911	7,911
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Weighting	Yes	Yes	Yes	Yes

Notes: The dependent variables are net outmigration ratio in columns (1) and (2), and destination-based immigration ratio in columns (3) and (4). Net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and deaths. Destination-based immigration ratio is defined as the percent of population aged 15 to 60 entering the county with their hukou in the origin. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population aged 15-60 in 1995. In columns (1) and (3), we include both $PM_{2.5}$ and SO_2 in one regression and instrument them using both thermal inversion strengths and numbers. In columns (2) and (4), we construct a single pollution index –Air Quality Index (AQI) –to incorporate two pollutants into one measurement. AQI is then instrumented by thermal inversion strengths. SW F-statistics are Sanderson-Windmeijer F-statistics for test of weak instruments for each endogenous variable. The Stock-Yogo weak identification F test critical values for single endogenous regressor at 10% maximal IV size is 19.93. Standard errors are listed in parentheses and clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Robustness Checks

	Baseline	Alternative clustering	Alternative fixed effects	Alternative weights	Alternative layer of inversion	Alternative definition of inversion	Interaction between region and weather
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Net out.							
$PM_{2.5}$	0.5309***	0.5309**	0.9356**	0.4776***	0.4407***	0.5074***	0.6098**
	(0.1762)	(0.2143)	(0.4126)	(0.1694)	(0.1486)	(0.1762)	(0.2563)
KP F-statistics	250.9	69.62	120	269.7	355	239	26.99
Panel B: Net out.							
SO_2	1.5433***	1.5433**	4.6619**	1.4123***	1.2953***	1.4968***	1.7940**
	(0.5123)	(0.6126)	(2.2372)	(0.4984)	(0.4361)	(0.5199)	(0.8522)
KP F-statistics	135.4	35.02	18.76	132	181.6	125.4	5.934
Panel C: Imm.							
$PM_{2.5}$	-0.3247***	-0.3247**	-0.4290**	-0.3342***	-0.1278**	-0.3528***	-0.5481***
	(0.0820)	(0.1381)	(0.1678)	(0.0852)	(0.0631)	(0.0855)	(0.1188)
KP F-statistics	250.9	69.62	120	269.7	355	239	26.99
Panel D: Imm.							
SO_2	-0.9439***	-0.9439**	-2.1375**	-0.9883***	-0.3756**	-1.0408***	-1.6126***
	(0.2486)	(0.4291)	(0.9595)	(0.2648)	(0.1883)	(0.2649)	(0.5155)
KP F-statistics	135.4	35.02	18.76	132	181.6	125.4	5.934
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	No	Yes	Yes	Yes	Yes
Period-by-province FE	No	No	Yes	No	No	No	No
Weighting	Pop in 1995	Pop in 1995	Pop in 1995	Average pop	Pop in 1995	Pop in 1995	Pop in 1995
Clustering	County	Prefecture	County	County	County	County	County
IV	Strength	Strength	Strength	Strength	Strength	Days	Strength
Layers	1 and 2	1 and 2	1 and 2	1 and 2	1 and 3	1 and 2	1 and 2

Notes: The dependent variables are net outmigration ratio in panels A and B, and destination-based immigration ratio in panels C and D. Column (1) is the baseline model. In column (2), we cluster the standard errors at prefecture level. In column (3), we replace period FE with period-by-province FE. In column (4), we weight regression using averaged population aged 15-60 during 1996-2010. In column (5), we calculate thermal inversion using layers at 110 and 540 meters. In column (6), we replace IV from thermal inversion strengths to number of days with thermal inversion. In column (7), we add interactions between region dummies and weather variables. Standard errors are listed in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Online Appendix

A.1 Data Details

Below we describe the details on how we calculate the destination-based immigrants. In the 2000 Census, the question on hukou status (**R061**) includes:

1. Living in this township,[21] hukou is in this township
2. Living in this township for more than 6 months, hukou is outside the township
3. Living in this township for less than 6 months, leave the place of hukou for more than 6 months
4. Living in this township, hukou status not determined
5. Originally living in this township, now study or work abroad, does not own hukou.

For options 2 and 3, there are further options regarding the place of hukou: (**R062**)

1. Other township (xiang) in this county
2. Other town (zhen) in this county
3. Other subdistrict (jiedao) in this county
4. Other township (xiang) in this district[22]
5. Other town (zhen) in this district
6. Other subdistrict (jiedao) in this district
7. Other counties or districts in this province

[21] Township is smaller administrative level than county, which includes three forms: subdistrict (jiedao), town (zhen), and township (xiang). Subdistrict is mainly used in cities, while town and township are mainly used in suburbs and rural areas

[22] District is the equivalent to county in terms of administrative level. It is mainly used in cities.

8. Outside this province.

There is one question regarding when do you live in this township (**R9**). The options are:

1. Since born
2. Before October 31th, 1995
3. November 1^{st} to December 31th, 1995
4. 1996
5. 1997
6. 1998
7. 1999
8. 2000.

There is one question (**R10**) asked where do you move (origin) to this township. The options are:

1. Within this county
2. Outside this county (specify the province, prefecture, and county name).

We determine if a person is a destination-based immigrant (living in the current address for more than six months based on NBS definition) during the past five years who does not transfer the hukou based on the following conditions:[23]

- R061 $= 2$
- R062 ≥ 7
- R9 ≥ 3.

[23] The 2000 Census date is November 1^{st}, 2000.

We can also determine if a person is a destination-based immigrant who transfers the hukou based on the following conditions:

- $1 \leq \text{R061} \leq 2$
- $1 \leq \text{R062} \leq 6$
- $3 \leq \text{R09} \leq 8$
- $\text{R10} = 2$.

The 2005 survey changed several questions. Specifically, the question on hukou status (**R06**) has the following options:

1. This township
2. Other township in this county
3. Other counties (specify the province, prefecture, and county name)
4. Undetermined.

The question **R08** asked when do you leave the place of hukou, and has the following options:

1. Never leave
2. Less than six months
3. Six months to one year
4. One to two years
5. Two to three years
6. Three to four years
7. Four to five years

8. Five to six years

9. More than six years.

Unfortunately, the 2005 Survey did not ask question on the specific living address before moving to this county (question R10 in the 2000 Census). Instead, it asked the living address five years ago (November 1^{st}, 2000) and has two options (**R15**):

1. Within this province

2. Outside this province (specify the province name).

We determine if a person is a destination-based immigrant who does not transfer the hukou during the past five years based on the following conditions:

- R06 $= 3$

- $3 \leq$ R08 ≤ 7.

There are several drawbacks of our definition. First, suppose a person's hukou is in county A, and he moved from county A to county B seven years ago, and moved from county B to county C three years ago. By our definition, he should not be counted as an immigrant for county C because he does not meet the condition for question R08, but he should be counted as an immigrant. This issue arises from question R08, as it asked when do you leave your hukou, instead of when do you move to the current address in the 2000 Census. This makes us to undercount the destination-based immigrant.

Second, suppose a person's hukou is in county A, and he moved from county A to county B four years ago, and moved from county B to county C three years ago, this person is counted an immigrant for county C based on our definition, but he should also be counted as an immigrant for county B. In other words, we can only capture the final immigration status, not the intermediate steps.

Third, suppose a person's hukou is in county A, and he moved from county A to county B four years ago, and lives in county B ever since. In the survey date (November 1^{st}, 2005), he is temporally live in county C for business. Then based on our definition, this person is regarded as an immigrant in county C, but he should be counted as an immigrant in county B.

We determine if a person is a destination-based immigrant who transfers the hukou based during the past five years based on the following conditions:

- $1 \leq$ R06 ≤ 2
- R08 = 1
- R15 = 2.

Noted this only captures the immigrant from outside provinces, as question R015 does not report the specific living address before moving.

For 2010 Census, the questions on hukou status are similar to the 2005 Survey. To our best knowledge, no individual-level data in 2010 are publicly available to researchers. Thus, we obtain the county aggregated data on destination-based immigrants. The drawbacks also exist for the 2010 data. Noted we cannot calculate origin-based outmigrants during 1996-2010 for two reasons. First, we only have the county aggregated data on destination-based immigrants in 2010. Second, the 2000 Census does not report the specific county name of the hukou. In other words, we can only calculate the origin-based outmigrants in 2005, which we cannot run regressions using the fixed effects model.

A.2 Comparison between AOD-based and Station-based Pollution Data

We use AOD-based pollution data in this paper because station-based data for specific air pollutants are only available after 2013. Before that, the Air Quality Index (AQI), which incorporates major air pollutants are only available for a few cities. Our station-based data are obtained from web-scratching of the China National Environmental Monitoring Center

(CNEMC), an affiliates to the Ministry of Environmental Protection of China. CNEMC reports real-time hourly AQI and specific air pollutants for around 1,000 monitoring stations.[24] We convert hourly station-based data to county using the IDW method in which we choose 100 km radius. We then collapse to month level to compare with AOD-based $PM_{2.5}$ and SO_2.

To start, we plot the monthly trend between AOD-based data (in black) and station-based data (in blue) over the period 2013-2015 for $PM_{2.5}$ in Figure A.8 and SO_2 in Figure A.9. We plot for the whole country as well as major cities across China including Beijing, Chongqing, Guangzhou, Harbin, Shanghai, Tianjin, Xi'an, and Wuhan. Though there are systemically difference between AOD-based and station-based data, the trend fits reasonably well.

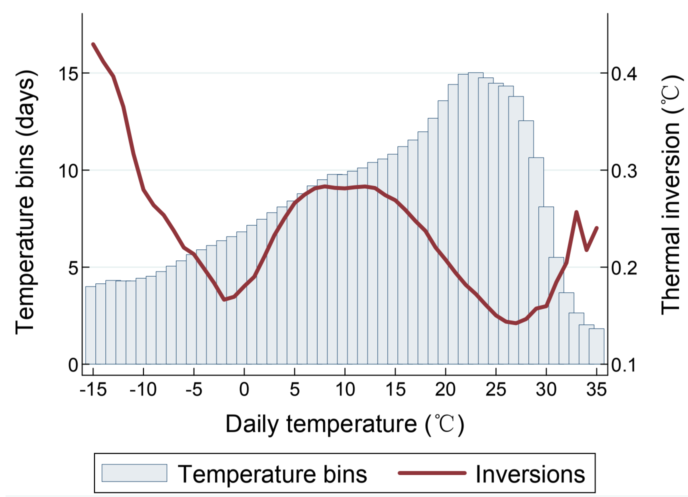
We then conduct a formal statistical test between two sources of data in Table A.12. The unit of observation is county-year. Column (1) reports the national average of two pollutants for years 2013, 2014, and 2015 separately and jointly for AOD-based data. Standard deviations are presented in the parenthesis. Similarly, column (2) reports the ground-based data. Column (3) reports the difference between two sources of data, and the standard errors are presented in the parenthesis. We find all the differences are statistically significant at 1% level. However, these differences may be caused by the county-specific differences. Therefore, we report the difference conditional on county fixed effects and year fixed effects in column (4). All the differences are gone. Because in our baseline model, we include county fixed effects and period fixed effects, AOD-based data is thus a good proxy for station-based data. We test the robustness by altering radius from 100 km to 50 km in column (5) and to 150 km in column (6) for the IDW method. We weight the test by population in 1995 in column (7). Our results are robust.

[24]The data can be viewed at http://106.37.208.233:20035/.

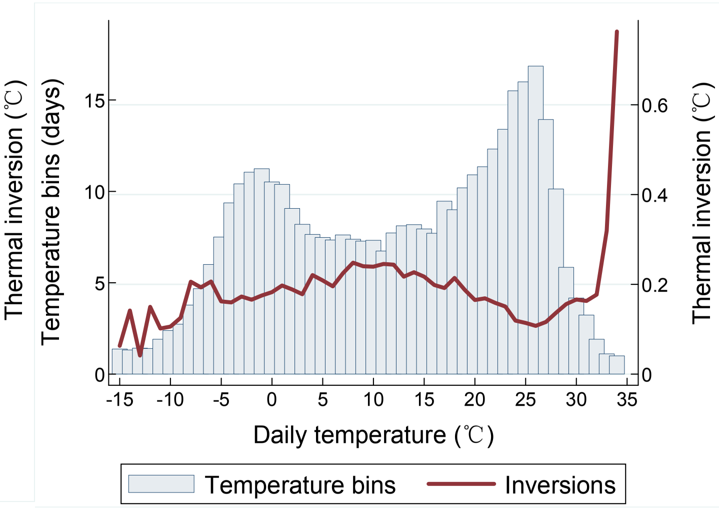
A.3 Tables and Figures

Figure A.7: Correlation between Temperature Bins and Thermal Inversions

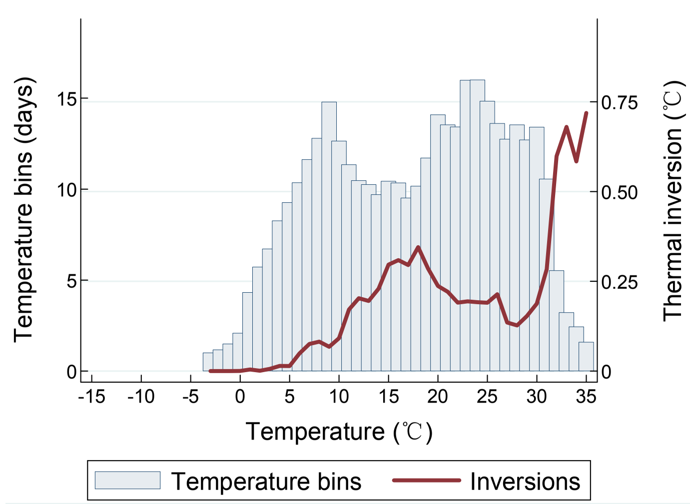
Panel A: National Average



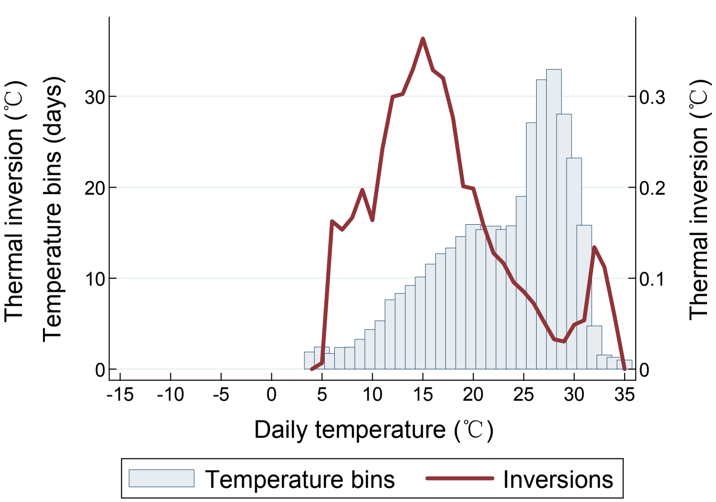
Panel B: Beijing



Panel C: Shanghai

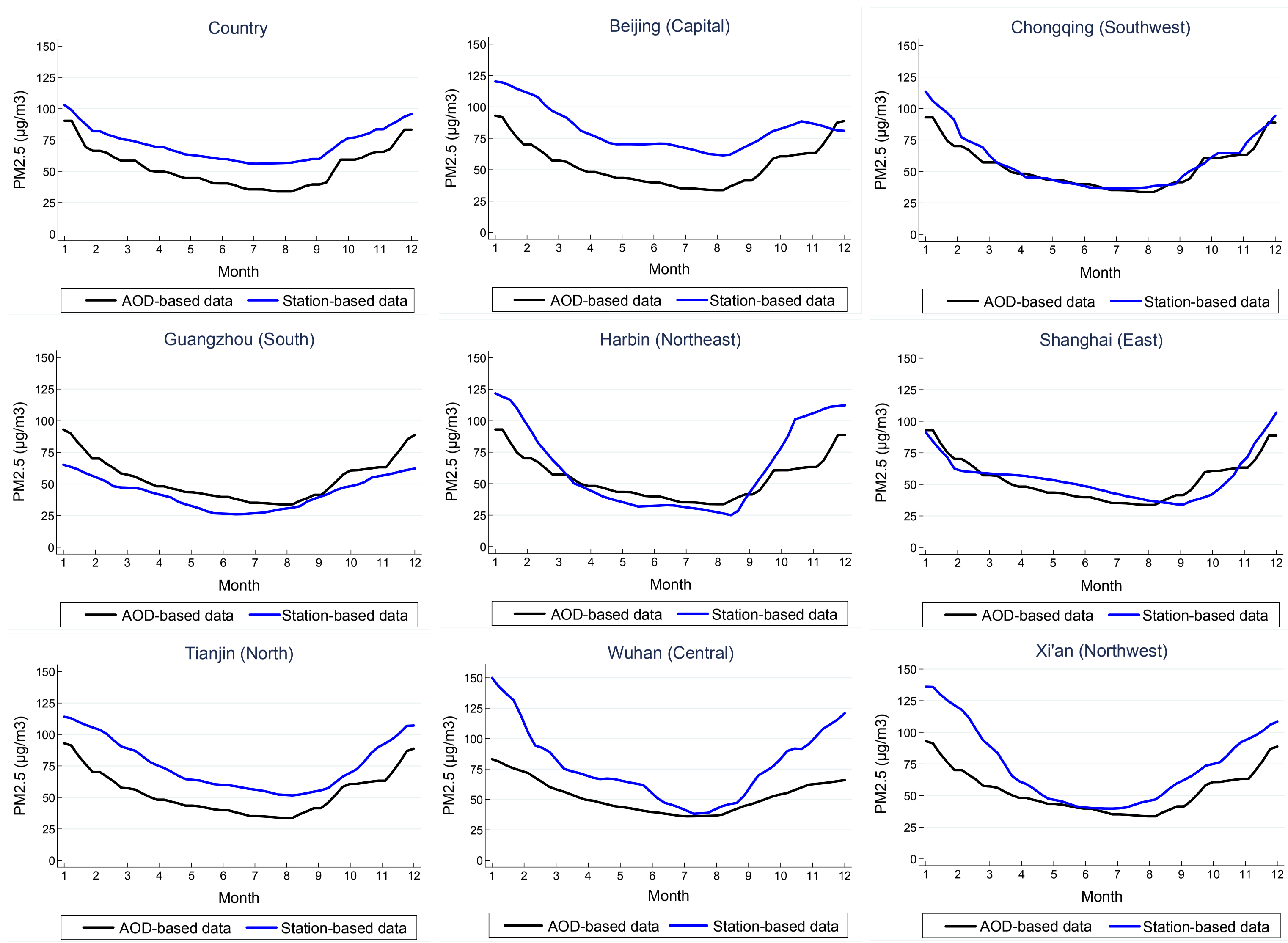


Panel D: Tianjin



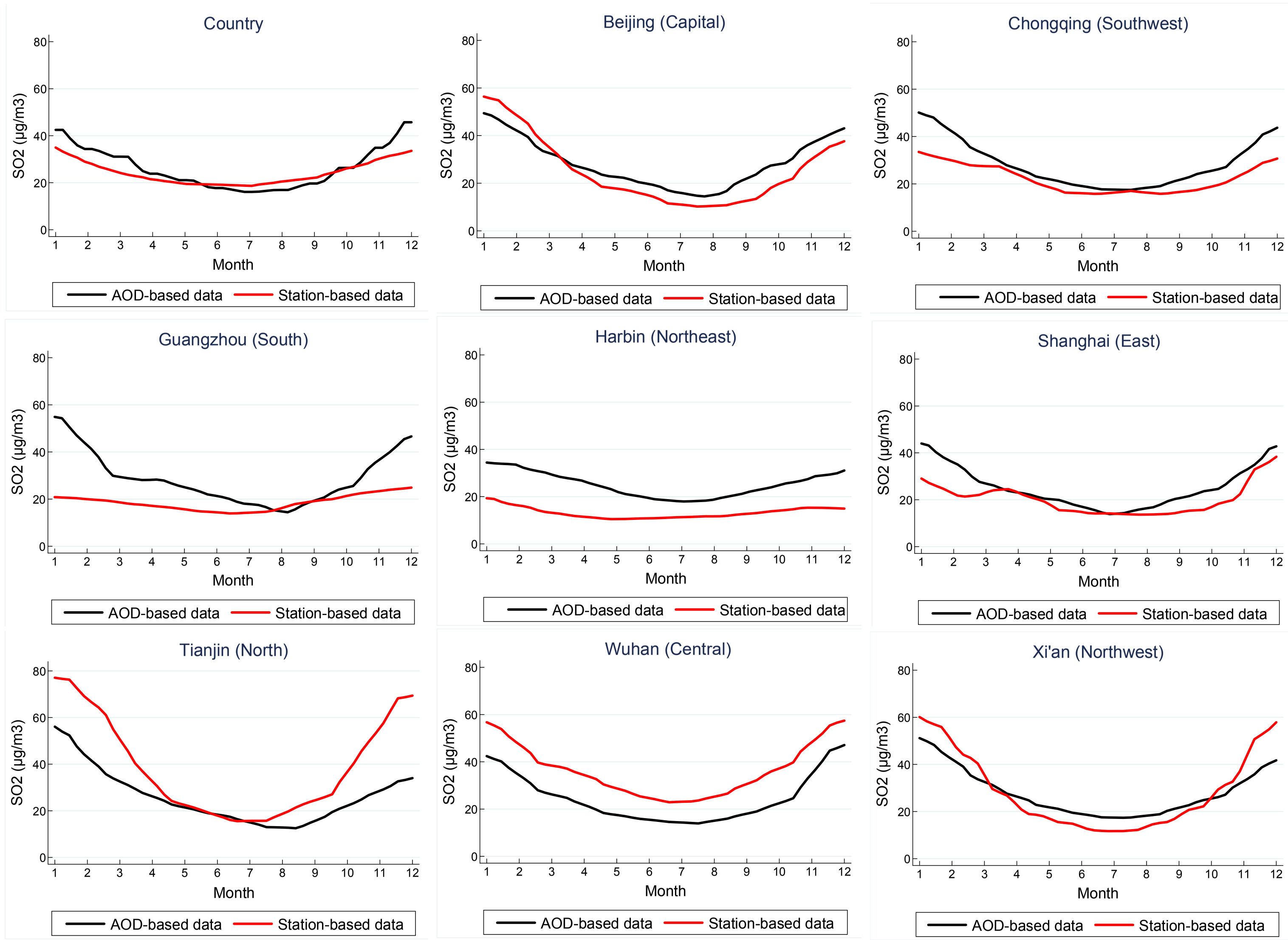
Notes: This figure plots the number of days and thermal inversion strength within each 1°C temperature bin. Panel A is the national average. Panels B, C, D are calculated using Beijing, Shanghai, and Guangzhou, respectively.

Figure A.8: Monthly Trend between AOD-based and Ground-based $PM_{2.5}$



Notes: This figure plots monthly trend between AOD-based and ground-based $PM_{2.5}$ for the country and major cities.

Figure A.9: Monthly Trend between AOD-based Data and Ground-based SO_2



Notes: This figure plots monthly trend between AOD-based and ground-based SO_2 for the country and major cities.

Table A.10: The Effect of PM $_{2.5}$ on Death Rates

	Years	All ages (1)	Age below 15 (2)	Age between 15-60 (3)	Age above 60 (4)
Average $PM_{2.5}$	0	0.0182	0.0341*	-0.0034	-0.1842
		(0.0264)	(0.0185)	(0.0130)	(0.1418)
KP F-statistics		77.20	57.87	70.16	73.11
Average $PM_{2.5}$	0-1	0.0041	0.0014	-0.0084	-0.1112
		(0.0228)	(0.0213)	(0.0104)	(0.1250)
KP F-statistics		74.49	52.14	65.92	69.15
Average $PM_{2.5}$	0-2	0.0536*	0.0358*	0.0041	0.1796
		(0.0295)	(0.0194)	(0.0132)	(0.1401)
KP F-statistics		65.90	58.55	61.37	65.79
Average $PM_{2.5}$	0-3	0.0755***	0.0388**	-0.0009	0.4653***
		(0.0243)	(0.0171)	(0.0104)	(0.1241)
KP F-statistics		75.30	62.95	71.44	76.03
Average $PM_{2.5}$	0-4	0.0660***	0.0398***	0.0040	0.4090***
		(0.0172)	(0.0091)	(0.0070)	(0.0872)
KP F-statistics		164.3	187	152.2	180.4

Notes: Number of observation is 7,911. The dependent variable is death rates (‰) in years 2000, 2005, and 2010. Regression models include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population in each age group in 1995. To incorporate lagged effect of air pollution, we calculate the average of each air pollutant across years. For example, average $PM_{2.5}$ with years 0 indicates the contemporaneous $PM_{2.5}$, while average $PM_{2.5}$ with years 0-1 indicates the average between contemporaneous and lagged one year. Average $PM_{2.5}$ with other years can be interpreted in the same manner. We instrument the average air pollutant using thermal inversion in the corresponding years. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A.11: The Effect of SO_2 on Death Rates

	Years	All ages (1)	Age below 15 (2)	Age between 15-60 (3)	Age above 60 (4)
Average SO_2	0	0.0413	0.0899*	-0.0076	-0.4015
		(0.0600)	(0.0496)	(0.0295)	(0.3118)
KP F-statistics		52.25	28.21	46.93	49.17
Average SO_2	0-1	0.0094	0.0037	-0.0191	-0.2387
		(0.0519)	(0.0577)	(0.0238)	(0.2689)
KP F-statistics		53.57	23.11	47.55	53.56
Average SO_2	0-2	0.1305*	0.1056*	0.0100	0.4178
		(0.0731)	(0.0574)	(0.0317)	(0.3284)
KP F-statistics		45.79	25.24	44.11	46.55
Average SO_2	0-3	0.2509***	0.1536**	-0.0031	1.5192***
		(0.0883)	(0.0713)	(0.0343)	(0.4608)
KP F-statistics		28.99	15.59	28.72	27.73
Average SO_2	0-4	0.1884***	0.1217***	0.0112	1.1812***
		(0.0516)	(0.0282)	(0.0199)	(0.2715)
KP F-statistics		95.93	82.08	94.98	93.31

Notes: Number of observation is 7,911. The dependent variable is death rates (‰) in years 2000, 2005, and 2010. Regression models include county fixed effects, period fixed effects, and flexible weather controls. Weather controls include temperature bins within 1°C, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Regression models are weighted using population in each age group in 1995. To incorporate lagged effect of air pollution, we calculate the average of each air pollutant across years. For example, average SO_2 with years 0 indicates the contemporaneous SO_2, while average SO_2 with years 0-1 indicates the average between contemporaneous and lagged one year. Average SO_2 with other years can be interpreted in the same manner. We instrument the average air pollutant using thermal inversion in the corresponding years. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A.12: Statistical Test Between AOD-based and Ground-based Pollution Data

	(1) AOD	(2) Station	(3) Unconditional difference	(4) Conditional difference	(5) Conditional difference	(6) Conditional difference	(7) Conditional difference
2013							
$PM_{2.5}$	55.0431	73.1464	-18.1034***	-0.0431	0.0547	-0.0411	-0.0444
	(29.5806)	(32.1741)	(0.7907)	(0.3641)	(0.6014)	(0.3219)	(0.3642)
SO_2	30.4324	25.5718	4.8606***	0.0185	0.0715	0.0132	0.0184
	(19.2522)	(15.1402)	(0.4639)	(0.2234)	(0.3918)	(0.2042)	(0.2236)
Obs	2,495	2,495	2,495	2,495	1,162	2,606	2,495
2014							
$PM_{2.5}$	62.7323	73.6688	-10.9364***	0.0118	0.2181	-0.0081	0.0124
	(19.6609)	(31.9031)	(0.4666)	(0.1891)	(0.3297)	(0.1652)	(0.1892)
SO_2	34.3568	25.5075	8.8492***	0.0277	0.1119	0.0171	0.0276
	(17.0051)	(15.0186)	(19.2242)	(0.1284)	(0.1881)	(0.1204)	(0.1285)
Obs	2,500	2,500	2,500	2,500	1,194	2,608	2,500
2015							
$PM_{2.5}$	49.9473	72.4348	-22.4875***	0.0287	-0.3274	0.0496	0.0295
	(16.2949)	(33.0719)	(0.4700)	(0.2139)	(0.3399)	(0.1952)	(0.2140)
SO_2	25.1135	26.0457	-0.9323***	-0.0462	-0.1951	-0.0302	-0.0459
	(12.8326)	(15.8749)	(0.3343)	(0.1334)	(0.2635)	(0.1210)	(0.1335)
Obs	2,500	2,500	2,500	2,500	1,194	2,608	2,500
All							
$PM_{2.5}$	55.9081	73.0833	-17.1751***	-0.0008	-0.0188	0.0001	-0.0007
	(23.1578)	(32.3867)	(0.3479)	(0.1541)	(0.2531)	(0.1370)	(0.1543)
SO_2	29.9672	25.7084	4.2587***	0.0000	-0.0045	0.0000	0.0000
	(17.0016)	(15.3492)	(0.2342)	(0.0966)	(0.1682)	(0.0887)	(0.0967)
Obs	7,495	7,495	7,495	7,495	3,550	7,822	7,495
County FE	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes
Radius	100 km	100 km	100 km	100 km	50 km	150 km	100 km
Weighting	No	No	No	No	No	No	Yes

Notes: Unit of observation is county-year. Columns (1) and (2) reports the national average of AOD-based data and station-based data. Column (3) reports the unconditional difference. Columns (4)-(7) reports the difference conditional on county fixed effects and year fixed effects. Standard deviations are listed in parentheses in columns (1) and (2) and standard errors are listed in parentheses through columns (3)-(7). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.