The Effect of Air Pollution on Migration: Evidence from China

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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. Specifically, we find that a 10 percent increase in air pollution, holding everything else constant, is capable of reducing population through net outmigration by about 2.8 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 strong gender asymmetries in the response of mid-age adults that suggests families are splitting across counties to protect vulnerable members of the household. Our results are robust to different specifications, including a spatial lag model that accounts for localized migration spillovers and spatially correlated pollution shocks.

Keywords: Air Pollution, migration, human capital, avoidance behaviour

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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 and adult mortality, hospitalization rates, health expenditures, hours worked, labor productivity, labor market decisions, test scores, and mental health (Chay and Greenstone, 2003; Currie et al., 2009; 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; Deschenes, Greenstone, and Shapiro, 2017; Chen, Oliva, and Zhang, 2018). 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; Ebenstein et al., 2017) as well as long-run impacts of in-utero exposure (Adhvaryu et al., 2016; Molina, 2016; Isen, Rossin-Slater, and Walker, 2017). 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 U.S. through hedonic methods (Chay and Greenstone, 2005). Given 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

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

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 distorted by market failures and regulation, causing further departures from the assumptions underlying hedonic methods. This is especially salient in China, where migration decisions have been heavily constrained by the household registration (*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 through semi-permanent adaptation measures. Also, zooming into the demographic composition of these flows helps us understand how the willingness to pay for air pollution might differ across socio-economic groups and how pollution-related migration can change the composition of the labor force across cities (Hanlon, 2016; Heblich, Trew, and Yanos, 2016). Our results also contribute to a sizable literature that 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, 2018). As our results show, migration flows related to air pollution are of similar magnitude to those projected based on plausible climate change scenarios (Feng, Oppenheimer, and Schlenker, 2015).

To our best knowledge, we are the first to estimate the causal effect of air pollution on migration flows. 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 medium to long-run impacts 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 overcoming the first empirical challenge is to use five-year variation in the average strength of thermal inversions within counties. Thermal inversions have been 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), labor productivity (Fu, Viard, and Zhang, 2017), and mental health (Chen, Oliva, and Zhang, 2018). 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. 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, as our evidence on the response to these shocks suggests, individuals update their beliefs about local air pollution using medium-run changes in air pollution concentration regardless of their source.

We overcome the second challenge, the data constraints on migration decisions, 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. Using census questions that are common across all census rounds, we are able to construct two separate measures of migration flows at the county level: net-outmigration and un-registered (floating) immigration.

Another innovation of our paper is the use of satellite-based particulate matter with a diameter of less than 2.5 μm ($PM_{2.5}$) 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 $PM_{2.5}$ model-based measures that incorporate Aerosol Optical Depth (AOD) measures and also historical analysis of the hydrological cycle as inputs, have been successfully validated vs. ground monitors in the atmospheric literature (Buchard et al., 2016).[2] 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.

[2] Although satellite-based AOD measures are only available from 2000 on, the MERRA-2 product that we use for this paper also incorporates AOD measures from Advanced Very High Resolution Radiometer (AVHRR) as inputs, which are available for the previous decade.

Our findings suggest that air pollution is responsible for large changes in inflows and outflows of migration in China. Specifically, we find that changes in air pollution that are independent across counties lead to changes in population at a rate of 2.8 percent reduction per 10 percent increase in air pollution. Of this change, about half corresponds to reduced immigration by floating migrants (which constitutes the bulk of the migration observed in our data). We find that these migration responses 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 between 30 and 45 years of age, but not men, migrate in response to air pollution at a rate of 5.8 percent of the population per 10 increase in air pollution (twice as much as the average adult). The differential response by gender in this cohort is consistent with families living apart in order to protect young children. Our results are robust to different specifications, including a spatial lag model that allows for spillovers and spatial correlation, 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.

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.[3]

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 five 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.[4] 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 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

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

[4] Note that deaths themselves may 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.

recent pollution levels at their destination, which is informative about the level of sophistication in an 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. 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, and Zhejiang), the Pearl River Delta (Guangdong), and the Jing-Jin-Ji Area (Beijing, Tianjin, and 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. Additional reason that these regions have large net outmigration ratio is that population (the denominator) in these areas are small. 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 county-average concentrations measured in microgram per cubic meter ($\mu g/m^3$) of $PM_{2.5}$ in Panel A 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).

The concentrations of $PM_{2.5}$ have significantly increased over the period, in particular after 2001, when China became the world's factory. In 2015, the average concentration is 66.90 $\mu g/m^3$, which is nearly 7 times higher than the standard of 10 $\mu g/m^3$ of annual mean recommended by the WHO (WHO, 2005).

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.[5] 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,

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

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 and long-run effects of $PM_{2.5}$ on human health have been well documented in various studies (Dockery et al., 1993; Pope III and Dockery, 2006; EPA, 2009; Deryugina et al., 2016).

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 facemasks (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 that those cities with high economic activity that attract immigrants by offering highly paid jobs are also those 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 that is difficult to reverse and very costly. Thus, we expect individuals to react slowly to perceive permanent changes in air pollution, and importantly, to react to changes that are observable over long periods. 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 five-year fluctuations in the strength of thermal inversions in a given county. 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.

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 (Fu, Viard, and Zhang, 2017) and mental health in China (Chen, Oliva, and Zhang, 2018). This is, however, the first study that uses thermal inversions to produce medium-run variation in air pollution by aggregating counts and computing average strength of inversions over five year periods. Although the variation in air pollution stemming from thermal inversions eventually reverts to the mean (i.e. does not generate permanent changes in air pollution), 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. Figure 4 illustrates the different sources of variation in air pollution. The hypothetical figure distinguishes between changes in air pollution generated by factors other than thermal inversions (solid dark lines) and all changes in air pollution (solid light lines) in two different counties. The difference between each pair of solid lines corresponds to the changes generated exclusively by thermal inversions. The casual observer can only keep track of the light lines, which contain all sources of changes in air pollution. Note that there is no public information on which share of the observed air pollution is generated by a transitory meteorological factors and which share is permanent. Hence, it is likely that after observing an inversion driven concentration change like the one highlighted in the graph, the observer will update her air pollution expectation (see dashed lines) even if the change is transitory.

The source of variation in air pollution that we use is also relevant for the interpretation of the magnitude of the results. Note that the thermal-inversion-related air pollution shocks that each county experiences are independent across counties. In fact, we test for independence of these shocks using a spatial lag model (discussed in Section 4.3 and in the Online Appendix Tables A2-A4). Thus, the effect we find can be interpreted as the migration response to a pollution shock in one county, everything else equal (i.e., keeping pollution constant everywhere else). In reality, the bulk of pollution changes were in the form of long-run permanent trends that were highly correlated across counties. Thus, our estimates are only applicable to the share of variation in pollution that was independent across counties. Although this is a small share of the variation, it is likely that these uncorrelated changes produced the most movement, as they generated starker trade-offs between locations. Because our estimates correspond to responses to uncorrelated changes in pollution, it is important to keep in mind that multiplying our estimated response by the total change in air pollution that occurred in a given county over any given period will produce an overestimate of the migration flow in response to that total change. Therefore, we refrain from extrapolating our results to computing the migration response to total changes in air pollution occurred in the period of our study.

3.1 Econometric Model

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

$$M_{ct} = \beta_0 + \beta_1 P_{ct} + f(\boldsymbol{W}_{ct}) + \gamma_c + \sigma_t + \varepsilon_{ct} \quad (1)$$

$$P_{ct} = \alpha_0 + \alpha_1 TI_{ct} + f(\boldsymbol{W}_{ct}) + \gamma_c + \sigma_t + \mu_{ct}, \quad (2)$$

where M_{ct} denotes two measures of migration in county c and period t: the net outmigration ratio, which is the fraction of people leaving a county minus new arrivals and deaths, and destination-based immigration ratio, which is the fraction of people entering a county but with their *hukou* in the origin. We define each period as a five-year interval. Thus, we have three periods in our study: 1996-2000 (period one), 2001-2005 (period two), and 2006-2010 (period three).

P_{ct}, measures the 5-year average concentration of $PM_{2.5}$, and we treat it as endogenous. Equation (2) shows the first stage of our empirical strategy. We instrument air pollution with the average strength of thermal inversions over each five-year period, TI_{ct}, conditional on flexible functions of weather variables ($\boldsymbol{W}_{ct}$), county fixed effects (γ_c), and period fixed effects σ_t. 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 measures of individual inversions are then averaged from six-hour to five-year period. In Section 3.2, we provide a detailed description of the source of information for thermal inversions as well as migration and pollution measures.

As argued above, thermal inversions generate county-level variation in air pollution concentrations that is independent of structural sources of air pollution, including economic development. To illustrate the lack of correlation between thermal inversions and country-wide changes in air pollution, Panel A in Figure 2 plots the county-average strength of thermal inversions in Celsius degrees (°C) in China over the period 1980-2015 along with $PM_{2.5}$ levels.[6] In contrast to air pollutants, there is no steep change in thermal inversion strength. This is especially important after 2001, when the steep increase in $PM_{2.5}$ was tied to rapid economic growth, as shown in Panel B of Figure 2. Thus, this figure backs up the exogeneity assumption of our instrumental variable with respect pollution sources associated with economic activity.[7] Nevertheless, to be overly cautious about spurious correlations between air pollution and thermal inversions over time, we include period fixed effects, σ_t, in all our specifications.[8]

There are a couple of additional considerations 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 Figure A2 in the Online Appendix 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

[6] See paragraph below for the definition of thermal inversion strength.

[7] We also plot the time trend of $PM_{2.5}$, thermal inversions, and GDP for three major cities in China: Beijing, Shanghai, and Guangzhou in Figure A1 of the Online Appendix. These figures show that, although spikes of air pollution sometimes coincide with spikes in inversion strength, there are no local trends in inversions that coincide with the broad direction of economic growth and air pollution.

[8] Our results are robust to the exclusion of period fixed effects, and as we show in the robustness section, to the inclusion of region specific period fixed effects.

temperature and inversion strength for Beijing, Shanghai, and Guangzhou, respectively. The regional variation in the 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 including 1 °C daily temperature bins, and second-degree polynomials in precipitation, sunshine duration, relative humidity, and wind speed.[9] Our identification strategy thus relies on the variation in the five-year average strength of thermal inversions net of weather variation at ground level.

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 A3 in the Online Appendix depicts the annual average concentration of $PM_{2.5}$ 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 square), and above 0.24 °C (in triangle). These thresholds were defined based on the 33rd and 66th 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 $\mu g/m^3$, while is 50.0 $\mu g/m^3$ and 56.9 $\mu g/m^3$ for counties with 0.08-0.24 °C and above 0.24 °C strength, respectively. These permanent differences in air pollution may induce self-selection patterns across regions that could potentially result in differences in migration rates. For

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

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 inversion-related variation in air pollution to deviations from the within-county average strength of thermal inversions over the course of fifteen years.

Figure 5 contrasts the cross-sectional variation with the within-county variation we are using in a map. While the map in Panel A shows the wide-spread geographic variation in average strength of thermal inversions (which are absorbed by our county fixed effects), Panel B shows that there is also a substantial amount of within-county variation in our period of study. More specifically, Panel B shows the difference between the minimum and maximum 5-year average strength of inversions in the 15-year period of our study for every county. There are many counties distributed over all regions of China that had differences over time that are equivalent to a quarter of the overall standard deviation in our measure of thermal inversions (darkest shade in the graph).

Finally, we discuss two spatial considerations when using thermal inversions as a county-level instrument: spillovers and spatial correlation. First, a "treated county" (a county that experiences an abnormally strong spell of thermal inversions in a five-year period) could have a spillover effects over neighboring counties if the bulk of the migration in response to the pollution shock in question goes to a small number of nearby counties. If this were the case, our estimates of the response to an independent pollution shock would be biased as some of the neighboring counties would in fact have some form of treatment. Second, assuming that the thermal inversion shocks are independent across space might be problematic as neighboring counties might share geographies and weather realizations that could make them similarly susceptible to a thermal inversion shock at a given time. To address these concerns, we (a) estimate a spatial lag model, where we explicitly account for shocks to nearby counties in the estimation, and (b) explore several standard error structures that can account for spatial correlation. In addition, we use population weights to correct for heteroscedasticity, as large population differences across counties will lead to differences in the precision of calculated migration rates.

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 of floating migrants. Since 1990, China has conducted decennial population census in 1990, 2000, and 2010, and the 1% population sample survey in 1995, 2005, and 2015. For our study, we use 1% and 20% individual-level data randomly drawn from the 2000 and 2005 censuses respectively, and county-aggregated data in 1995 and 2010 from National Bureau of Statistics (NBS) of China.[10]

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

[10] To the best of our knowledge, no individual-level census data in 1995 and 2010 are publicly available.

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 five-year interval using the following equation:

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

where $NetOutmig_{c,t}$ is the net outmigration ratio for those aged [15, 60] during the five-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 $D\widehat{[15{,}60]}$ represents an approximate measure of deaths for the same population during the five-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 outmigration ratio in two ways. The first way omits deaths from calculation in Equation (1). 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 to five years as the right hand side variable of interest. Results of this specification are shown in Table A1 in the Online Appendix. 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 statistically insignificant response to air pollution. These findings across age groups are consistent with prior literature on 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 per thousand, 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 in Figure 6, 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).

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.[11] 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. 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 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.[12] The data are reported at each 0.5 degree × 0.625 degree (around 50 km × 60 km) latitude by longitude grid in each month since 1980. The concentration of $PM_{2.5}$ is calculated following Buchard et al. (2016). The monthly

[11] Our calculation comes from the 2000 Census, which has information on both floating and registered migration.
[12] The data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary.

pollution data are then aggregated from grid to county. We then average to annual level across all months and further average to each five-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 covered 42 cities in 2000 and 86 cities in 2010, while AOD-based data cover the whole country. 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 specific air pollutants and manipulation is not a major concern[13]. We find no statistical difference between them conditional on county fixed effects. The details are discussed in the Online Appendix. Table 1 shows descriptive statistics for $PM_{2.5}$. The average concentration of $PM_{2.5}$ during 1996-2010 is 53.08 $\mu g/m^3$, which is five times larger than the WHO's standard.

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

[13] 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.

50 km × 60 km) grid, and records the six-hour air temperature at 42 layers, ranging from 110 meters to 36,000 meters.[14] 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 layer (110 meters). If the difference is positive, there exists a 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 six-hour lapses within each five-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. The average strength during our study period is 0.22 °C. During 1996-2010, average thermal inversion strength appears to be increasing at a very slow pace in average.

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.[15] We then average relative humidity, and wind speed, and aggregate precipitation and sunshine duration across days within each year and further average to each five-year period. We also construct the number of days within each 1 °C temperature bin and aggregate over five-year periods.

[14] The data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2I6NPANA_V5.12.4/summary.

[15] 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.

4 Results

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

Table 2 presents the first-stage estimates of the effect of thermal inversions on $PM_{2.5}$ concentrations (Equation 2 in Section 3.1). All regressions control for county and period fixed effects as well as weather controls. Column (1) shows the results without population weights, while column (2) uses population aged 15 to 60 in 1995 to weight the regression.

We find significant and robust effects of thermal inversions on $PM_{2.5}$ concentrations. As the measure of thermal inversion strength is somewhat difficult to interpret in terms of magnitude, one can multiply the point estimates by 0.004 (0.22/53.08) 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. 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, of 16.38.

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

Panel A in Table 3 reports the estimates of air pollution on the net outmigration ratio with and without adjusting for approximate deaths. Recall that Table A1 in the Online Appendix 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) – (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 fixed effects (FE) 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.

We first discuss the results of air pollution on net-outmigration ratios without adjusting for deaths. The FE estimates in column (1) 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 FE 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 column (3), which weights the regression using population in 1995. It shows that the IV effect is nearly twice the size of the FE effect.

The magnitude of the effect of air pollution on net outmigration flows is large and economically significant. A ten percent increase in $PM_{2.5}$ (5.31 $\mu g/m^3$) reduces population by 2.8 per 100 inhabitants due to migration. Although it is tempting to apply these estimates to the increase in air pollution that the average county in China experienced over the 15 years of our study: 60 percent (27 $\mu g/m^3$), we caution against doing this, as the observed changes in air pollution were highly correlated across counties and our estimate corresponds to an independent change in air pollution. Nevertheless, we note that there was a substantial amount of uncorrelated variation in pollution over the time of our study. As Figure 3 illustrates, 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). As a way to assess the amount of variation in air pollution that is relevant for our migration response estimates, we also decomposed the overall time variation in air pollution into a common trend across counties and the remaining (uncorrelated) variation. The uncorrelated time variation is about 26% of the total time variation. Hence, even if our estimates apply just to the uncorrelated portion of the observed variation, our large point estimates still imply that the population movement in response to air pollution is economically meaningful.

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). First, the size of the standard errors vary little, suggesting that inference in unweighted regressions is not misleading. Second, the effect of $PM_{2.5}$ on net outmigration are similar, suggesting 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 costlier (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 place 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.

Panel B in Table 3 reports the estimates of $PM_{2.5}$ on immigration ratio. The FE 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). 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 $PM_{2.5}$ (5.31 $\mu g/m^3$) brings in 1.7 people per 100 inhabitants. The smaller magnitude of the effects compared to net outmigration ratios is 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) in Panel B 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 Robustness Checks

Here we discuss the results of several robustness checks: alternative forms of clustering standard errors, alternative fixed effects and controls, alternative weights, variations on the measure of thermal inversions, and a spatial lag model that accounts for potential localized spillovers and spatial correlation of standard errors.

Table 4 shows several of these additional results and compares them to our baseline (column 1). In the baseline, standard errors are clustered at county level (six-digit administrative code), which accounts for autocorrelation of the error terms over periods within each county. In column (2), we cluster standard errors at prefecture level (four-digit administrative code), 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. The KP *F*-statistic for weak instruments is quite lower, but still above the Stock-Yogo critical value for 10% relative bias.[16]

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) of Table 4, 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 ways of constructing our instrumental variable. 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 to 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.

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 A2 in the Online Appendix demonstrates,

[16] 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.

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 patterns across regions are being picked up by our instrument.

Finally, Online Appendix Tables A2 – A4 show the results of a spatial lag model that addresses several potential issues with our estimates stemming from the spatial proximity of some of these counties. First, if the bulk of migration in response to an air pollution shock (like the one generated by thermal inversions) goes to (or comes from) a small set of counties in close proximity to the shock-receiving county, our identification strategy would violate the stable unit treatment value assumption (SUTVA). This is because the treatment to one unit of observation (a pollution shock to one county) could cause nearby counties to experience meaningful atypical migration flows. If on the other hand, the migration response is dispersed over numerous counties, then SUTVA would not be violated. A spatial lag model is useful to test this assumption as it explicitly accounts for the effect on migration shocks to nearby counties. Because migration shocks to nearby counties are also endogenous, we instrument for them using thermal inversion shocks to them. The results of this model are presented in Online Appendix Table A2, where the spatial lag is created using the inverse distance weighted average of migration flows to neighboring counties. This variable is instrumented using a similarly weighted average of thermal inversion average strength. Columns (1) – (4) show the results of this model with net outmigration as the dependent variable and columns (5) – (8) show the results for immigration of floating migrants.[17] Note that the effect of local

[17] Standard errors are clustered at either the county level (columns 1, 2, 5, and 6) or at the prefecture level (columns 3, 4, 7, and 8). We do not use a spatially decaying correlation structure for the variance as the code

pollution on migration in all models remains of roughly the same magnitude as in our baseline and with similar levels of significance once we explicitly control for local spillovers. Consistent with this, the effect of the spatial lag of migration flows is insignificant in all models. Together, these results suggest that thermal inversion shocks are well spread out across counties as opposed to concentrated in a few neighboring counties.

Second, because weather shocks might be spatially correlated, thermal inversions could be more likely in counties in close proximity to a county that receives one. Although clustering at the prefecture level (like we do in column 2 of Table 4) could help approximate the correct error structure in this case, a spatial lag model would again fully account for this effect separately. Unfortunately, the correct variance structure for the IV spatial lag model, one where the correlation of the dependent variable decays with distance, is hard to estimate from scratch and generic code is not available. However, Tables A3 and Tables A4 estimate the first stage and reduced form of this IV model using the correct variance structure. In all cases the main results do not differ from our baseline, suggesting that localized spillovers and spatial correlation in the error term are not affecting our main estimates.

4.4 Heterogeneity by demographic groups

In the previous section, we find a robust and significant effect of air pollution on migration for the adult population in China. We argue that the effect we identify reflects the average response to perceived long-run air pollution changes. However, different individuals may have different tradeoffs between perceived harm from air pollution and economic opportunities. In particular, we expect that highly educated individuals will be better informed about potential harm from air

that incorporates both IV and this variance structure is currently unavailable. However, a variance structure with a spatially decaying correlation is studied in Online Appendix Tables A3 and A4, which correspond to the first stage and the reduced form of the IV model in Table A2.

pollution exposure and will also have lower costs of migration, as formal migration is within reach for this demographic group. Other heterogeneity in the response could stem from differences in vulnerability to air pollution: children and elderly face higher health impacts from poor air quality. In this section we exploit information on demographic characteristics to explore whether our main result masks any heterogeneity that is consistent with these relative tradeoffs.

4.4.1 Education and gender

We first explore whether the migration response varies by education level. Note that because we are focusing on individuals aged between 15 and 60, education is likely fixed for most of the adults in our sample. Highly educated individuals are likely to have a better understanding of the harmful effects of air pollution, which would increase their perceived benefit from migration. They are also likely to have higher income and more job opportunities as well as the ability to change their registration. This last set of factors are likely to lower the opportunity cost of migrating, again making the migration response to pollution more likely.

Panel A of Table 5 shows how our estimates of the effect on net outmigration vary by education and gender categories. The three categories of education level we explore are junior high school or below, high school, and college or above.[18] Although we find positive and significant effects of $PM_{2.5}$ on net outmigration ratio for all educational categories, there is a large degree of heterogeneity across education groups. Consistent with the relative tradeoffs described above, our results show that the migration response is monotonically increasing with 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.

[18] The data on immigration ratio by education level are not available.

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 economies and cause the so called "brain drain effect" (Fischer, 2003). In addition, our findings support other recent literature that finds effects of air pollution on the socioeconomic composition of neighborhoods (Hanlon, 2016; Heblich, Trew, and Yanos, 2016).

When looking at the results by education and gender categories, we find that the education gradient is more pronounced for males than for females. In particular, females with the lowest level of education we consider are still more likely to migrate in response to air pollution than the average adult in China. In contrast, males in this education category are not migrating in response to pollution according to our estimates. Also note that regardless of the education level, women are more likely to migrate than men. This pattern could emerge from a lower labor force participation of women combined with the ability of families to live in separate counties. It could also stem from women migrating away from their husband along with the children they take care of in order to protect them from the harmful effects of air pollution. In the next section we explore whether it is women in young and mid adulthood that have stronger responses, which would be consistent with split families.

4.4.2 Age and gender

The expected relative size of the migration effect by age is less clear than by education. On the one hand, younger adults may have lower opportunity costs of moving as their networks have not been established and many may be choosing the location of their very first job. They may also have younger children that are more vulnerable to air pollution. Both of these traits would lead younger individuals to migrate at higher rates in response to air pollution compared to older individuals. On the other hand, older adults will be closer in time to facing very harmful effects of air pollution as suggested by our results on deaths in Online Appendix Table A1. This would lead to higher responses from the older individuals in our sample.

We present the results by age in Panel B of Table 5. Our results show that young and mid-age adults are more likely to migrate in response to air pollution compared to older individuals. The split by gender provides an even more nuanced picture, showing that among females it is mid-age adults that are more likely to migrate, but among male it is the youngest cohort that is more mobile in response to air pollution. This pattern is again consistent with families being able to split across two locations in order to maximize both health benefits and economic gains.

Finally, our results by age provide an additional robustness check on the construction of our dependent variable. Given that we cannot properly account for deaths, the fact that the effect is the smallest for the oldest cohort is reassuring. If our effects were biased upwards by deaths being counted as out migrants, the bias would be strongest for the oldest group.

4.4.3 Results 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 relocation. Thus, this detail of the data allows 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 6 reports our results on destination-based immigration ratio 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. In other words, families could be unbundling the job and home location decisions. 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 insignificant, lending support to the notion that our instrument is unlikely to have effects on other determinants of migration.

4.4.4 Results by Occupation

In Table A5 in the Online Appendix, we estimate the effect of $PM_{2.5}$ on immigration ratio by occupations[19]. Panel A includes all immigrants regardless of their origins, while Panels B and C include immigrants from the same province and from different province respectively. Column (1) includes all occupations. Relative to our baseline estimate for all immigrants regardless whether they are employed or not (column (3) in Table 3), the effect for immigrants who are employed are larger, and most immigrants are from the same province.

Columns (2) – (7) report the effect on specific occupations, including government/party/enterprise leader, professionals, clerks, business/service, agriculture, and

[19] The data on net outmigration ratio by occupation are not available.

manufacturing[20]. We find the largest effect for immigrants working in the business and service sector. One possible reason is that they are easy to move. On the contrary, the effect is smallest for people in the agriculture sector, because they may be tied to the land.

4.5 Where did People Get Information on Air Pollution?

Our results on migration responses to air pollution indicate that individuals were able to keep track of recent changes in air pollution levels both in origin and destination counties. In order to confirm this, we explore whether counties that had air pollution monitors, and thus, objective public information on air pollution levels experienced sharper responses to air pollution.

Our sample period is from 1996 to 2010. Since 2000, the Ministry of Environmental Protection (MEP) published publicly available data on API, a piece-wise linear transformations of PM_{10}, SO_2, and NO_2. In 2000, there are only 47 cities with API data available. The number of cities with API data are then increased each year, and to 86 in 2010. We can therefore explore whether the effects are larger for cities with API data.

We report the results in Table A6 in the Online Appendix. Panels A and B include cities with API data, and Panels C and D include cities without API data. The dependent variables are net outmigration ratio in Panels A and C, and immigration ratio in Panels B and D. Column (1) is the baseline estimate, in which we include all cities. In columns (2) – (6), we only include cities with or without API data.

We find a much larger effect for cities with API data. For example, in column (6), we find that the effect on net outmigration ratio is twice larger for the 86 cities with API data than the remaining 250 cities without API data. The same conclusion holds when migration is measured by

[20] See detailed description of each occupation at http://ms.nvq.net.cn/nvqdbApp/htm/fenlei/index.html (in Chinese).

immigration ratio. These results are consistent with individuals responding to air pollution information, and suggest that people do incorporate the publicly available API data into their air pollution assessments.[21]

4.6 Measuring Air Pollution using Sulfur Dioxide (SO_2)

Our results so far have used $PM_{2.5}$ as the indicator for air pollution levels, since it is a major air pollutant in China and causes a variety of health problems. However, as it is true in other papers that use thermal inversions as a source of variation for air pollution, the observed effects could correspond to other pollutants that are also affected by thermal inversions. In order to explore whether our results will change if we use a different measure of air pollution, we use sulfur dioxide (SO_2) instead of $PM_{2.5}$ as the main pollutant of interest. The MERRA-2 dataset we used directly reports SO_2.

Table A7 in the Online Appendix reports the first-stage estimates on SO_2. We find that a 1 °C increase in average inversion strengths in a five-year period increases the concentrations of SO_2 by 24.95 μg/m^3. Converted to elasticities, we find that a 1 percent increase in inversion strength increases SO_2 concentrations by 0.36 percent[22], which is very similar to the elasticity of $PM_{2.5}$ (elasticity=0.33). Table A8 in the Online Appendix reports the second-stage estimates on the effect of SO_2 on migration. Our baseline model in column (6) suggests that a ten percent increase in SO_2 (1.54 μg/m^3) concentrations in one county induces 2.38 people moving out from that county net

[21] Another way to show the importance of air pollution data is to run the regression for periods without and with pollution data. However, because we only have three periods (1996-2000, 2001-2005, and 2006-2010) and API data are only available in 2000, we cannot run regression models for periods 1996-2000 since there is no within-county variation. We estimated regressions for periods 1996-2005 and 2001-2010, each with two five-year separately, and find a much larger effect for the latter periods. These results are available upon requests.

[22] The mean concentrations of SO_2 during our sample period is 15.39 μg/m^3.

out of new arrivals and deaths. The elasticity is quite similar to the elasticity with respect to $PM_{2.5}$ (2.82).

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. 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 A9 in the Online Appendix, in which migration is measured by net outmigration ratio in columns (1) and (2), and by immigration ratio 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, the AQI.

When we include both air pollutants in the model, we find insignificant 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 leading role. When we use destination-based immigration as our outcome variable, we find that the effect of $PM_{2.5}$ is weakly significant but the joint effect is 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 increased by 29.14 points. This suggests that counties that experienced a five-year change in pollution similar to the country's average saw a 12.44 percent (0.4269% × 29.14) drop in the adult population through migration in response to this increase (under the linearity and independence assumptions discussed above). Of this, 7.61 percentage points (-0.2611% × 29.14) 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 1).

4.7 Mechanisms

There could be two possible mechanisms through which air pollution affects people's migration decision. The first is individual-decision driven (or household-decision driven), which means that people voluntarily move to counties with better air quality because it is good for their or their family's health. The second is the firm or government-decision driven, which means that people move predominantly in response to a firm or a government's decision to relocate economic activity in response to air pollution. For example, Fu, Viard, and Zhang (2017) find that air pollution significantly lowers labor productivity in manufacturing firms in China. As a result, firms may move to clean places and those workers move along with firms.

To test whether this is the case, we utilize the Chinese Industrial Enterprises Database, the same dataset used in Fu, Viard, and Zhang (2017). This dataset covers all state-owned enterprises and non-state firms with sales above CNY 5 million and reports annual balance-sheet information from 1998 to 2007. Similar to our migration measure, we define five years as a period, namely, 1998-2002 as the first period, and 2003-2007 as the second period. We then construct the outmigration (immigration) ratio for each county as the ratio between number of firms moving out (in) and total number of firms at the beginning of each period. We calculate net outmigration ratio as the difference between outmigration and immigration ratio. We then estimate the effect of air pollution on three measures of firm migration using thermal inversions as the instrument and include county fixed effects, period fixed effects, and weather controls.

Table A10 in the Online Appendix reports the estimates. Column (1) includes all firms. Columns (2) – (5) reports the estimates for each ownership: state-owned, private, foreign, and hybrid. We do not find any significant effects of five-year average air pollution on any measure of migration for any ownerships. This is also consistent with Fu, Viard, and Zhang (2017), in which they do not find effect of annual average air pollution on firm's migration. Our results suggest that the migration in response to air pollution that we are capturing is predominantly driven by decisions at the individual or household level.

5 Discussion and Conclusions

Our findings suggest that pollution changes are an important determinant of internal migration in China. A county-level independent shock to air pollution of 10 percent of the average concentration will reduce the population in that county by 2.8 percent through a combination of less immigration and more outmigration. A significant share (close to half) of that response seems to be produced by reduced immigration of floating immigrants; i.e. immigrants that do not change their *hukou* or official residence when they move. This suggests that individuals keep track of air pollution levels not only in their county of origin but also in potential destination counties.

When interpreting the magnitude of our results, it is important to account for the independence of the shocks that we use to identify our effects. This is relevant because pollution changes in China in the period of our study were highly correlated across counties. Specifically, out of the average time variation in our pollution data (that is, the average variation left after subtracting the cross-sectional variation), only 26 percent is uncorrelated across counties. Therefore, extrapolating our estimates to the total changes in air pollution that the average county experienced would likely overestimate the movement in population that air pollution was responsible for in this period. However, even when assuming that the correlated portion of the variation in this period did not result in any migration across counties, our effects suggest significant changes in population in response to air pollution. Specifically, we can multiply our preferred estimate times the standard deviation of the uncorrelated variation, 6.93, to get the percentage reduction in population a county would experience from an independent shock to air pollution of typical size. This calculation yields a net-outmigration impact of 3.68% of the population over the course of five years.

The magnitude of these flows is especially important when considering their demographic composition. Our results show that responses to air pollution are predominantly driven by women in childbearing and child-rising age and that their male counterparts migrate at lower rates (and only when they are very young). This suggests that families are choosing to split between different locations in response to air pollution; a result that had not been documented in the literature. In addition, the migration response to air pollution has a steep education gradient. This has the potential to reshape the labor force composition across counties.

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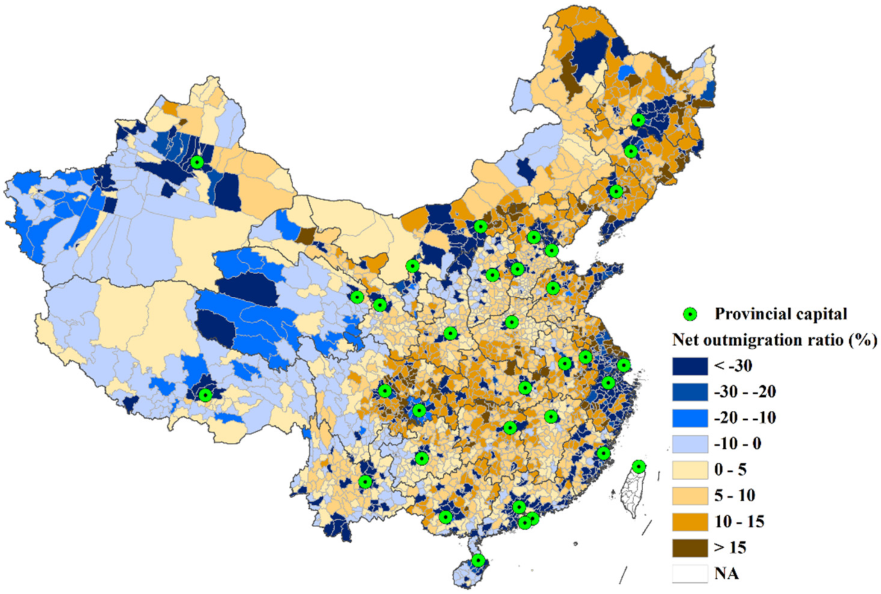
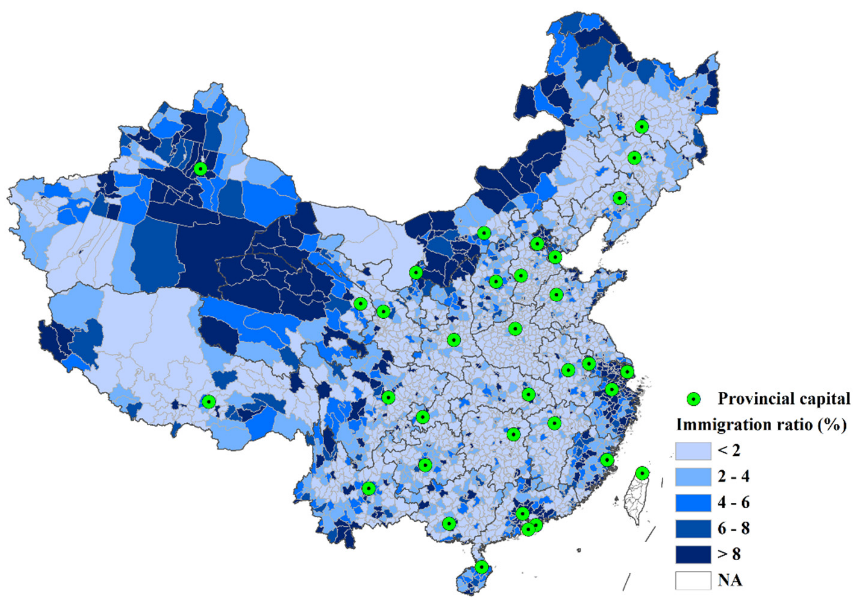
Tables and Figures



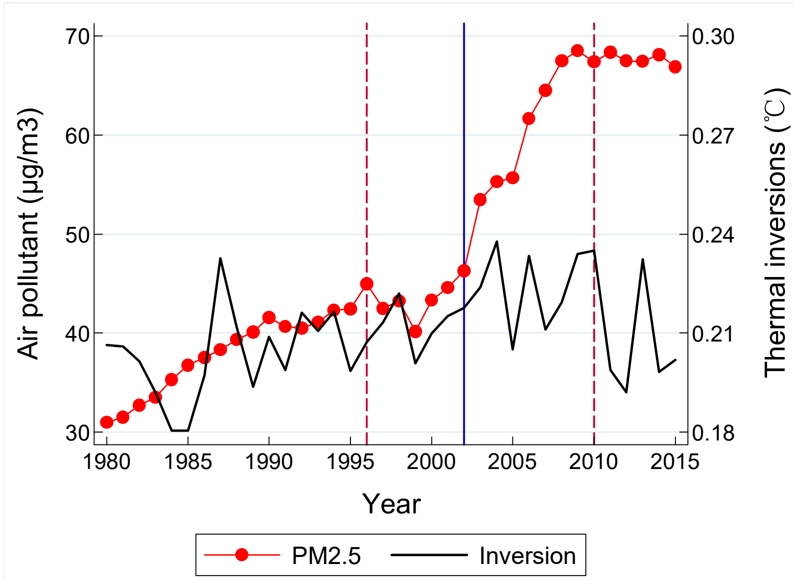
Panel A: Net Outmigration Ratio



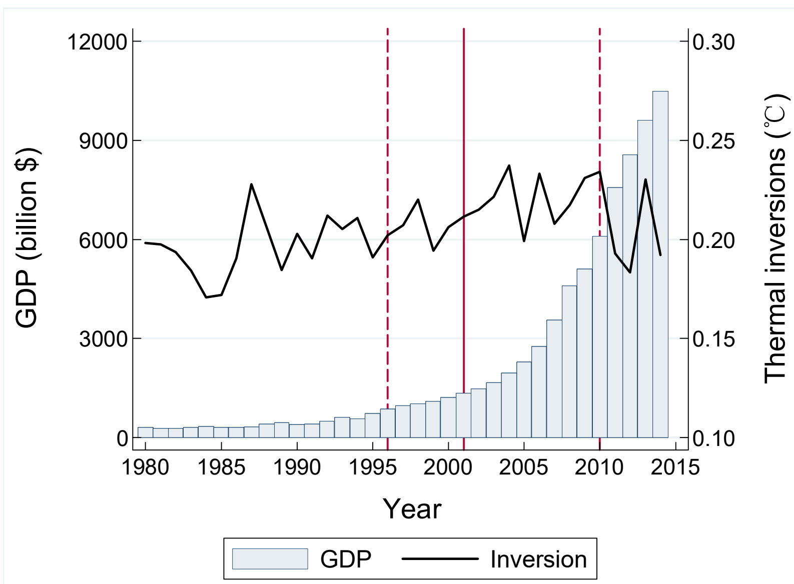
Panel B: Immigration Ratio

Figure 1: Migration in China (1996-2010)

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.



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



Panel B: GDP and Thermal Inversion

Figure 2: Time Trend of $PM_{2.5}$, Thermal Inversions, and GDP in China (1980-2015)

Notes: This figure depicts the national average of $PM_{2.5}$ and thermal inversions in Panel A and GDP and thermal inversions in Panel B in each year during 1980-2015.

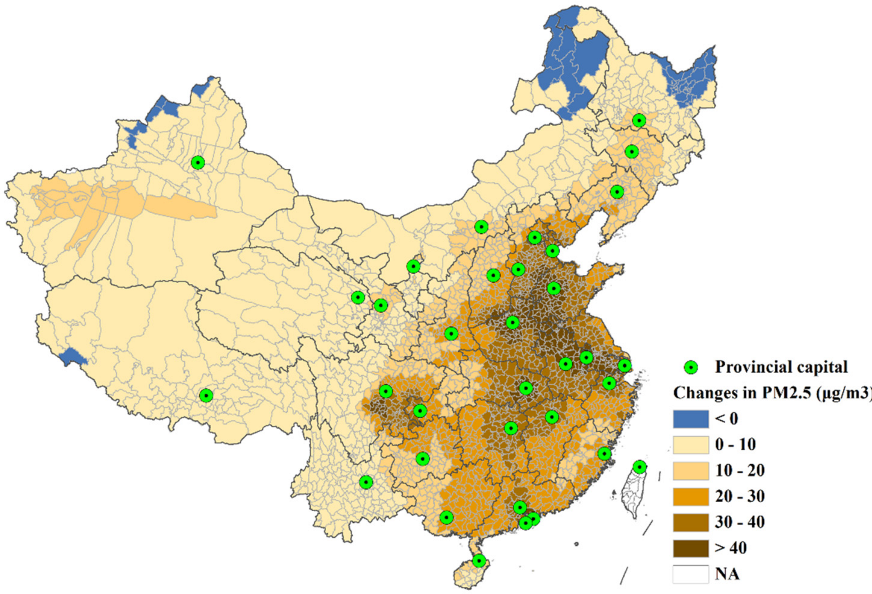


Figure 3: Pollution Changes in China (1996-2010)

Notes: This figure depicts the changes in $PM_{2.5}$ concentrations between the period 1996-2000 and 2005-2010 for each county in China.

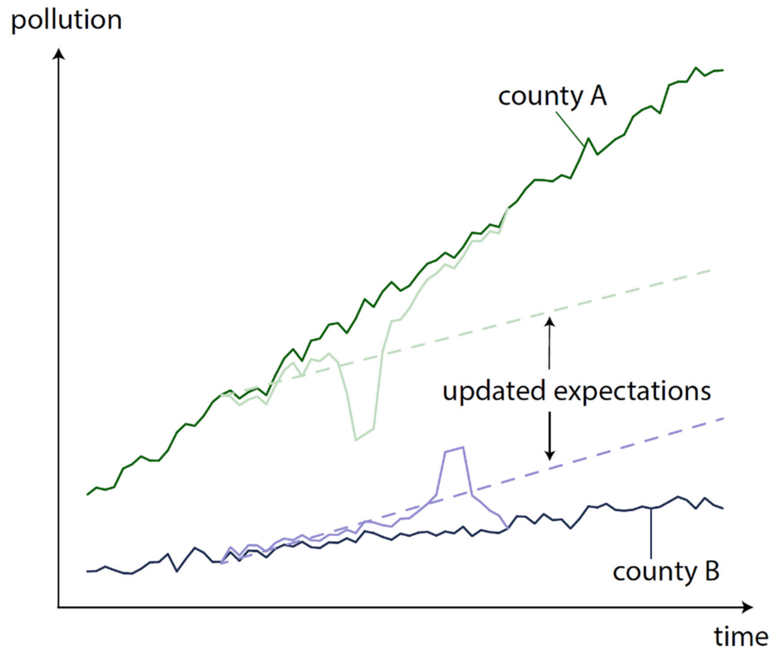
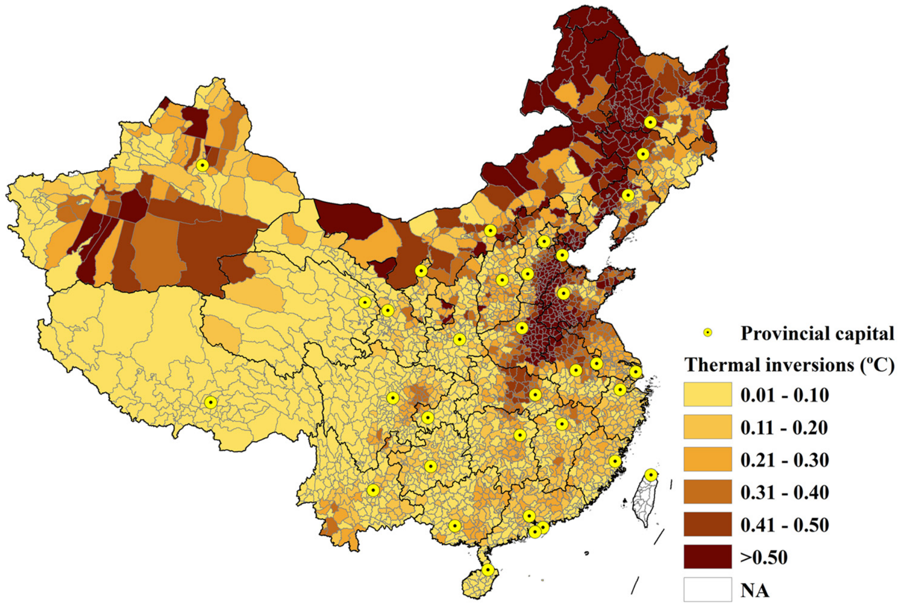
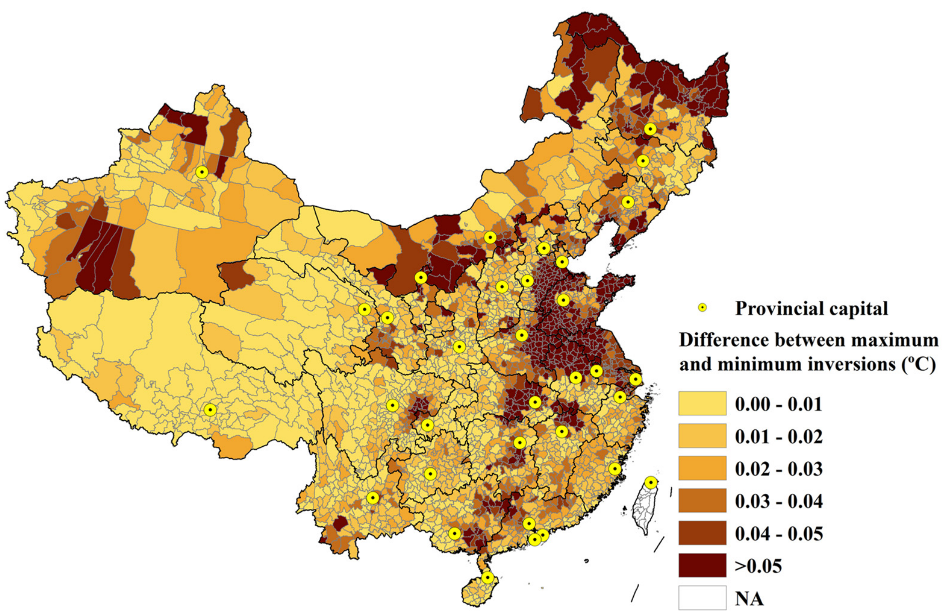


Figure 4: Expectation

Notes: This figure illustrates the formation of expectations about air pollution in the presence of pollution shocks generated by thermal inversions. We thank Tamma Carleton, our discussant at the Occasional Conference in UCSB, for providing it.



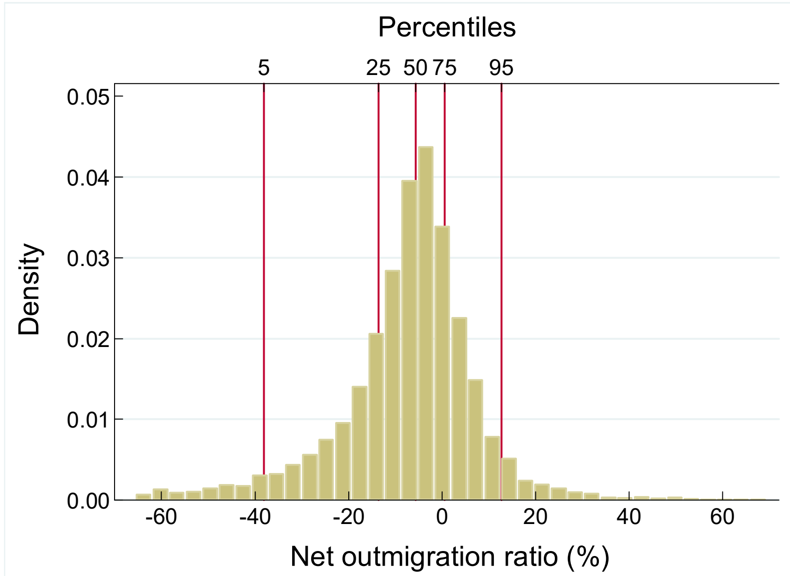
Panel A: Average of thermal inversions (ºC) during 1996-2010



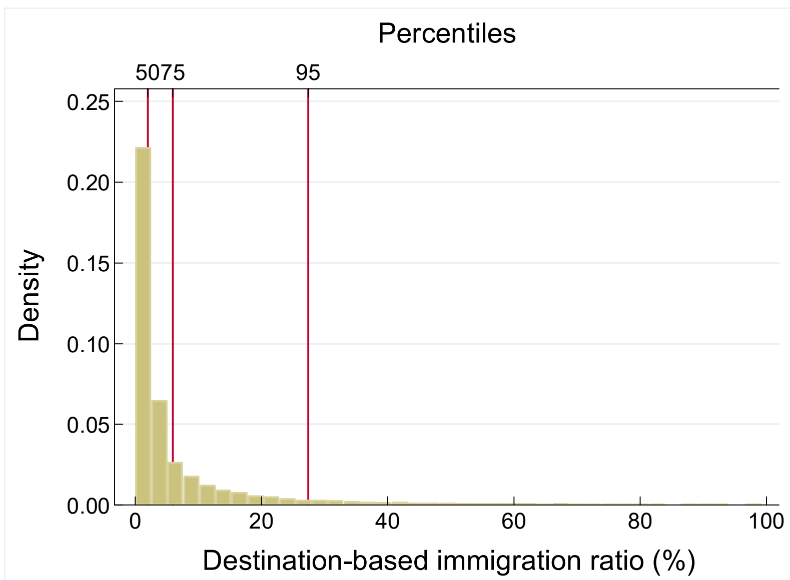
Panel B: Difference between maximum and minimum inversions (ºC)

Figure 5: Thermal inversions (1996-2010)

Notes: Panel A depicts the average of thermal inversions for each county during 1996-2010. Panel B depicts the difference between maximum and minimum inversions for each county during the same period.



Panel A: Net Outmigration Ratio with Death Adjustment



Panel B: Immigration Ratio

Figure 6: Histogram of Net Outmigration Ratio and 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.

Table 1: Summary Statistics

Variable	Unit	1996-2010		1996-2000		2001-2005		2006-2010	
		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
Immigration ratio	%	6.01	10.73	3.41	6.16	4.20	7.49	10.40	14.90
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
Thermal inversion									
Strength	°C	0.22	0.19	0.21	0.19	0.22	0.20	0.23	0.20
Number of inversions	Days	107.65	59.00	107.30	56.87	107.03	59.63	108.62	60.47

Notes: The unit of observation is county-period (five years). 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. 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 six-hour period, and then is averaged for each period. Positive difference indicates an existence of a thermal inversion with magnitude representing the strength, while negative difference indicates a non-existence of a thermal inversion and is truncated to zero. Number of inversions is calculated using annual days with thermal inversions, and then averaged to the five-year period.

Table 2: The Effect of Inversions on $PM_{2.5}$ (First Stage)

	(1)	(2)
Thermal inversions	78.6938***	82.0176***
	(5.4654)	(5.1621)
KP *F*-statistics	865.2	984.9
Observations	7,911	7,911
County FE	Yes	Yes
Period FE	Yes	Yes
Weather controls	Yes	Yes
Weighting	No	Yes

Notes: The dependent variable is $PM_{2.5}$. Regression models are estimated using Equation (2) and include county fixed effects and period fixed effects. Weather controls include temperature bins within 1ºC, 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 (2). 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 $PM_{2.5}$ on Migration

	FE	IV		FE	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Net Outmigration Ratio						
	No death adjustment			Death adjustment		
$PM_{2.5}$	0.2898***	0.5797***	0.5161***	0.2967***	0.5944***	0.5314***
	(0.0584)	(0.1638)	(0.1743)	(0.0589)	(0.1657)	(0.1761)
KP *F*-statistics	----	205.9	250.7	----	205.9	250.7
Panel B: Immigration Ratio						
$PM_{2.5}$	0.1258***	-0.2516***	-0.3246***	----	----	----
	(0.0299)	(0.0679)	(0.0820)	----	----	----
KP *F*-statistics	----	205.9	250.7	----	----	----
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 variables are net outmigration ratio in Panel A and destination-based immigration ratio in Panel B. Through columns (1) – (3), 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 (4) – (6), net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and death. The destination-based immigration ratio is defined as the percent of population aged 15 to 60 entering the county with their *hukou* in the origin. Columns (1) and (4) are fixed effects estimates, and columns (2) – (3) and (5) – (6) are IV estimates in which we instrument $PM_{2.5}$ using thermal inversions strength. Weather controls include temperature bins within 1 ºC, 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), (3), (4), and (6). Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table 4: Robustness Checks

	Baseline	Alternative clustering	Alternative fixed effects	Alternative weights	Alternative layer of inversions	Alternative definition of inversions	Interaction between region and weather
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Net Outmigration Ratio							
$PM_{2.5}$	0.5314***	0.5314**	0.9348**	0.4780***	0.4416***	0.5705***	0.6098**
	(0.1761)	(0.2143)	(0.4119)	(0.1694)	(0.1486)	(0.1842)	(0.2563)
KP *F*-statistics	250.7	69.60	120.4	269.6	354.7	229.1	26.99
Panel B: Immigration Ratio							
$PM_{2.5}$	-0.3246***	-0.3246**	-0.4275**	-0.3340***	-0.1280**	-0.3650***	-0.5481***
	(0.0820)	(0.1382)	(0.1675)	(0.0852)	(0.0631)	(0.0923)	(0.1188)
KP *F*-statistics	250.7	69.60	120.4	269.6	354.7	229.1	26.99
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 Panel A and destination-based immigration ratio in Panel B. Column (1) is the baseline model. In column (2), we cluster 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 inversions 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. All models include county fixed effects and temperature bins within 1 ºC, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. Standard errors are listed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 5: The Effect of PM2.5 on Net Outmigration Ratio: By Education, Gender, and Age

Panel A: By Education and Gender

	All gender				Males				Females			
	Full sample	Primary and below	Middle school	College and above	Full sample	Primary and below	Middle school	College and above	Full sample	Primary and below	Middle school	College and above
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$PM_{2.5}$	0.5314***	0.4723**	0.5736**	0.9314**	0.3600*	-0.2229	0.6480***	0.9192**	0.6977***	0.6975***	0.7910***	1.2369**
	(0.1761)	(0.2350)	(0.2427)	(0.4433)	(0.1935)	(0.3219)	(0.2429)	(0.4315)	(0.1846)	(0.2169)	(0.2742)	(0.5347)
KP F-stat.	250.7	300.9	224.2	169.7	250.7	305.3	226.6	171.6	250.7	304.1	224.4	172.1
Obs.	7,911	7662	7673	7617	7,911	7,699	7,692	7,621	7,911	7,712	7,655	7,595
Mean [SD]	-9.17	-1.59	-11.20	-17.03	-10.07	-7.18	-7.05	-10.01	-8.68	-0.04	-12.40	-18.97
of D.V.	[16.15]	[10.06]	[24.64]	[40.44]	[18.84]	[40.02]	[22.75]	[32.91]	[16.64]	[25.49]	[27.52]	[43.68]

Panel B: By Age and Gender

	All gender				Males				Females			
	Age 15-60	Age 15-30	Age 30-45	Age 45-60	Age 15-60	Age 15-30	Age 30-45	Age 45-60	Age 15-60	Age 15-30	Age 30-45	Age 45-60
$PM_{2.5}$	0.5314***	0.7446**	0.6905***	0.0470	0.3600*	0.7865**	0.2198	0.3536	0.6977***	0.8583***	1.1164***	-0.2131
	(0.1761)	(0.3173)	(0.2089)	(0.2555)	(0.1935)	(0.3774)	(0.2282)	(0.2737)	(0.1846)	(0.3274)	(0.2295)	(0.3034)
KP F-stat.	250.7	269.3	255.5	281	250.7	269.3	255.5	281.1	250.7	269.2	255.5	281
Obs.	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911
Mean [SD]	-9.17	-1.07	-7.62	-13.24	-10.07	-4.25	-8.61	-16.21	-8.68	-0.54	-9.37	-16.65
of D.V.	[16.15]	[31.16]	[23.15]	[13.21]	[18.84]	[40.15]	[25.31]	[14.65]	[16.64]	[30.65]	[26.98]	[13.02]

Notes: The dependent variable is net outmigration ratio by each group. 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 weather controls. Regression models are weighted using population for each group 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 $PM_{2.5}$ on Immigration Ratio: By Origins

	Total immigration	Across county within province	Across county outside province	Within county
	(1)	(2)	(3)	(4)
$PM_{2.5}$	-0.3246***	-0.1780***	-0.0851**	-0.0090
	(0.0820)	(0.0595)	(0.0409)	(0.0076)
KP F-statistics	250.7	250.7	250.7	250.7
Observations	7,911	7,911	7,911	7,911
Mean [SD] of D.V.	6.01 [10.73]	3.66 [6.72]	2.58 [5.93]	4.46 [2.96]

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. Column (1) includes all migrants regardless of origins. Column (2) includes migrants whose origins and destinations are in the same province. Column (3) includes migrants whose origins are outside the province of the destination. Column (4) includes migrants whose origins are in the same county of the destination but in another township. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and weather controls. 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.

Online Appendix

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[1], *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, and does not have *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[2]
5. Other town (*zhen*) in this district
6. Other subdistrict (*jiedao*) in this district
7. Other counties or districts in this province
8. Outside this province.

There is one question regarding when the person lives in this township (**R9**). The options are:

1. Since born

[1] Township is a 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.
[2] District is the equivalent to county in terms of administrative level (six digits). It is mainly used in cities.

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

There is one question (**R10**) asked what is the origin to this township. The options are:

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

We determine if a person is a destination-based immigrant (living in the current address for more than six months based on the NBS definition) during the past five years who does not transfer the *hukou* based on the following conditions:[3]

- R061=2
- R062>=7
- R9>=3.

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

- 1<=R061<=2
- 1<=R062<=6
- 3<=R09<=8

[3] The 2000 census date is November 1st, 2000.

- 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 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 census 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 1st, 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<=R08<=7.

There are several drawbacks of our definition. First, suppose a person's *hukou* is in county A, and he/she 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/she should not be counted as an immigrant for county C because he/she does not meet the condition for question R08, but he/she 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/she 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/she 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/she moved from county A to county B four years ago, and lives in county B ever since. In the survey date (November 1st, 2005), he/she is temporally living 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<=R06<=2
- R08=1
- R15=2.

Noted this only captures the immigrant from outside provinces, as question R15 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. Note 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.

2. Comparison between AOD-based and station-based pollution data

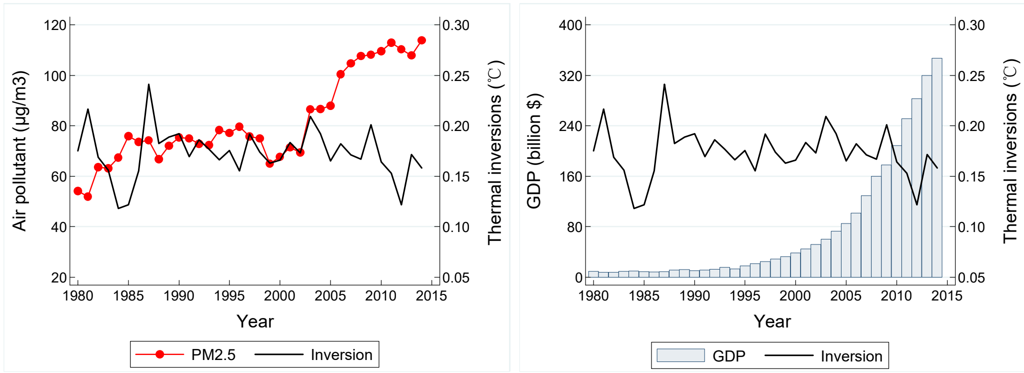
We use AOD-based pollution data in this paper because station-based data for specific air pollutants are only available after 2013. Before that, the Air Quality Index (AQI), which incorporates major air pollutants are only available for a few cities. Our station-based data are obtained from web-scratching 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[4]. 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 $PM_{2.5}$.

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 A4 in the Online Appendix. We plot for the whole country as well as major cities across China including Beijing, Shanghai,

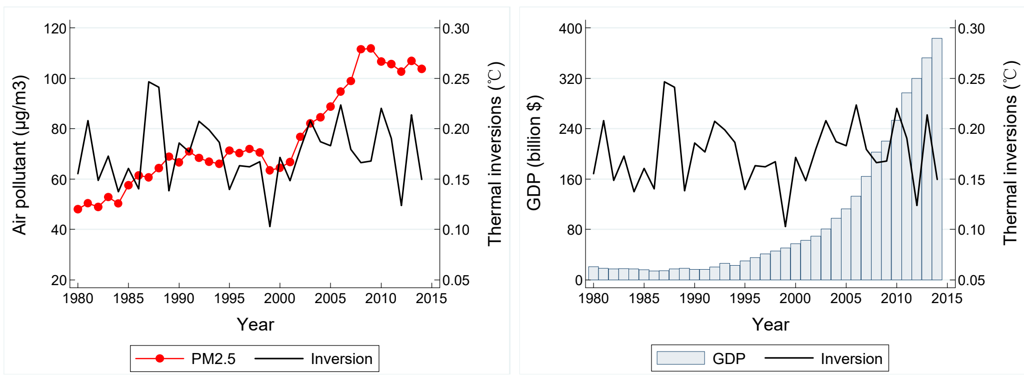
[4] The data can be viewed at http://106.37.208.233:20035.

Chongqing, Guangzhou, and Tianjin. Though there are systemically difference between AOD-based and station-based data, the trend fits reasonably well.

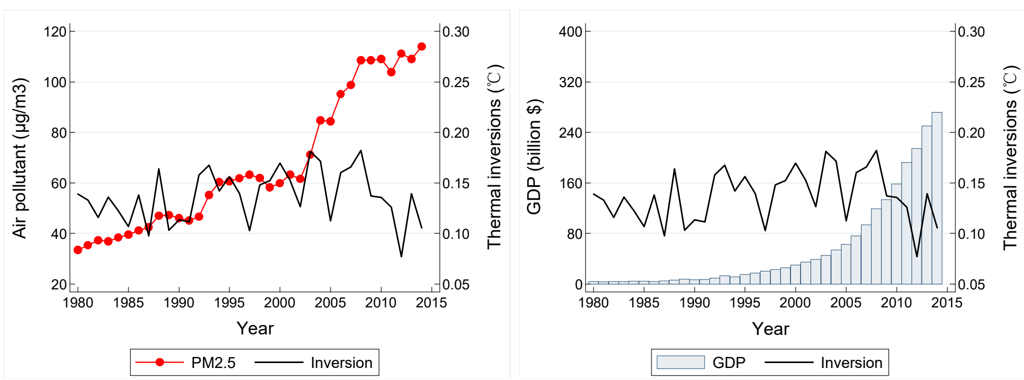
We then conduct a formal statistical test between two sources of data in Table A11 in the Online Appendix. The unit of observation is county-year. Column (1) reports the national average of two pollutants for years 2013, 2014, and 2015 separately and jointly for station-based data. Standard deviations are presented in the parenthesis. Similarly, column (2) reports the AOD-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 the 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 statistically insignificant. 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.



Panel A: Beijing



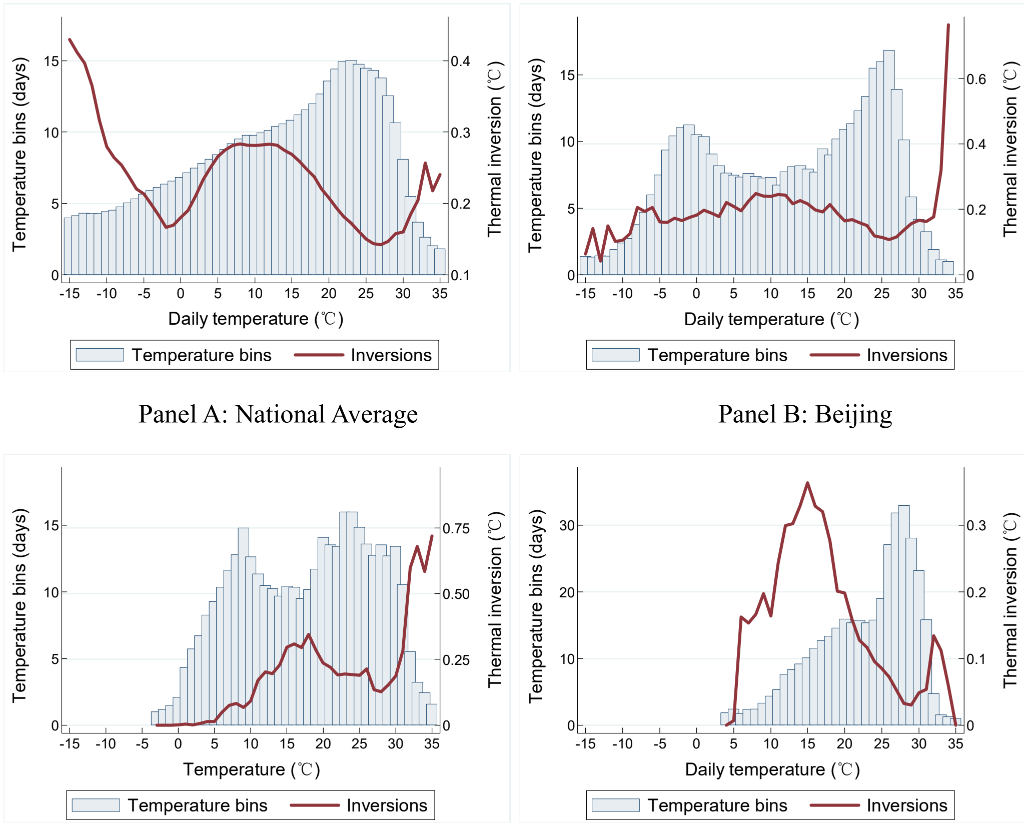
Panel B: Shanghai



Panel C: Guangzhou

Figure A1: Time Trend of $PM_{2.5}$, Thermal Inversions, and GDP in Beijing, Shanghai, and Guangzhou (1980-2015)

Notes: This figure depicts the average of $PM_{2.5}$, thermal inversions, and GDP for Beijing (Panel A), Shanghai (Panel B), and Guangzhou (Panel C) in each year during 1980-2015.



Panel A: National Average

Panel B: Beijing

Panel C: Shanghai

Panel D: Guangzhou

Figure A2: Correlation between Temperature Bins and Thermal Inversions

Notes: This figure plots the number of days and thermal inversion strength within each 1 °C temperature bin for the nation (Panel A), Beijing (Panel B), Shanghai (Panel C), and Guangzhou (Panel D).

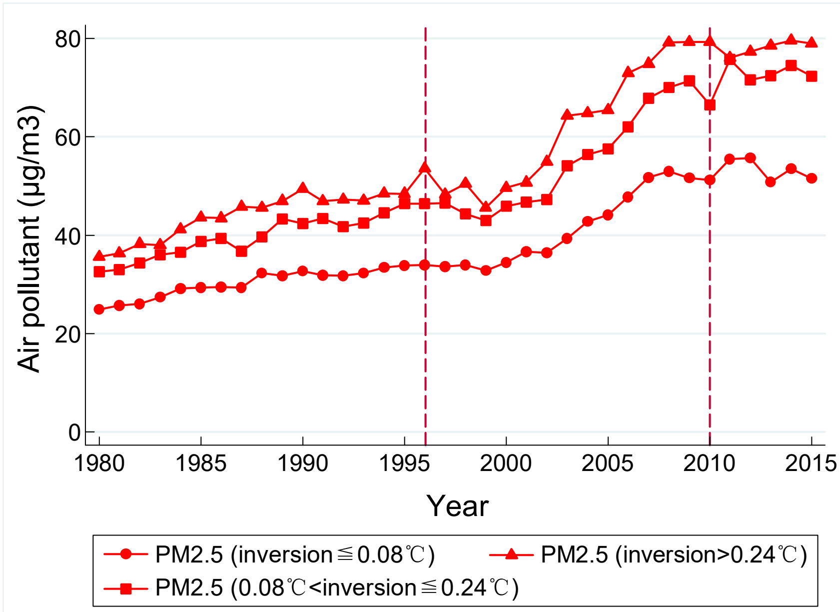


Figure A3: Time Trend of $PM_{2.5}$ by Strength of Thermal Inversions (1980-2015)

Notes: This figure plots the national average of $PM_{2.5}$ concentration in each year over the period 1980-2015 for three categories: thermal inversion strength less than 0.08 ºC (33th percentile), between 0.08 and 0.24 ºC (66th percentile), and above 0.24 ºC. Two red vertical lines highlight the course of our study: 1996-2010.

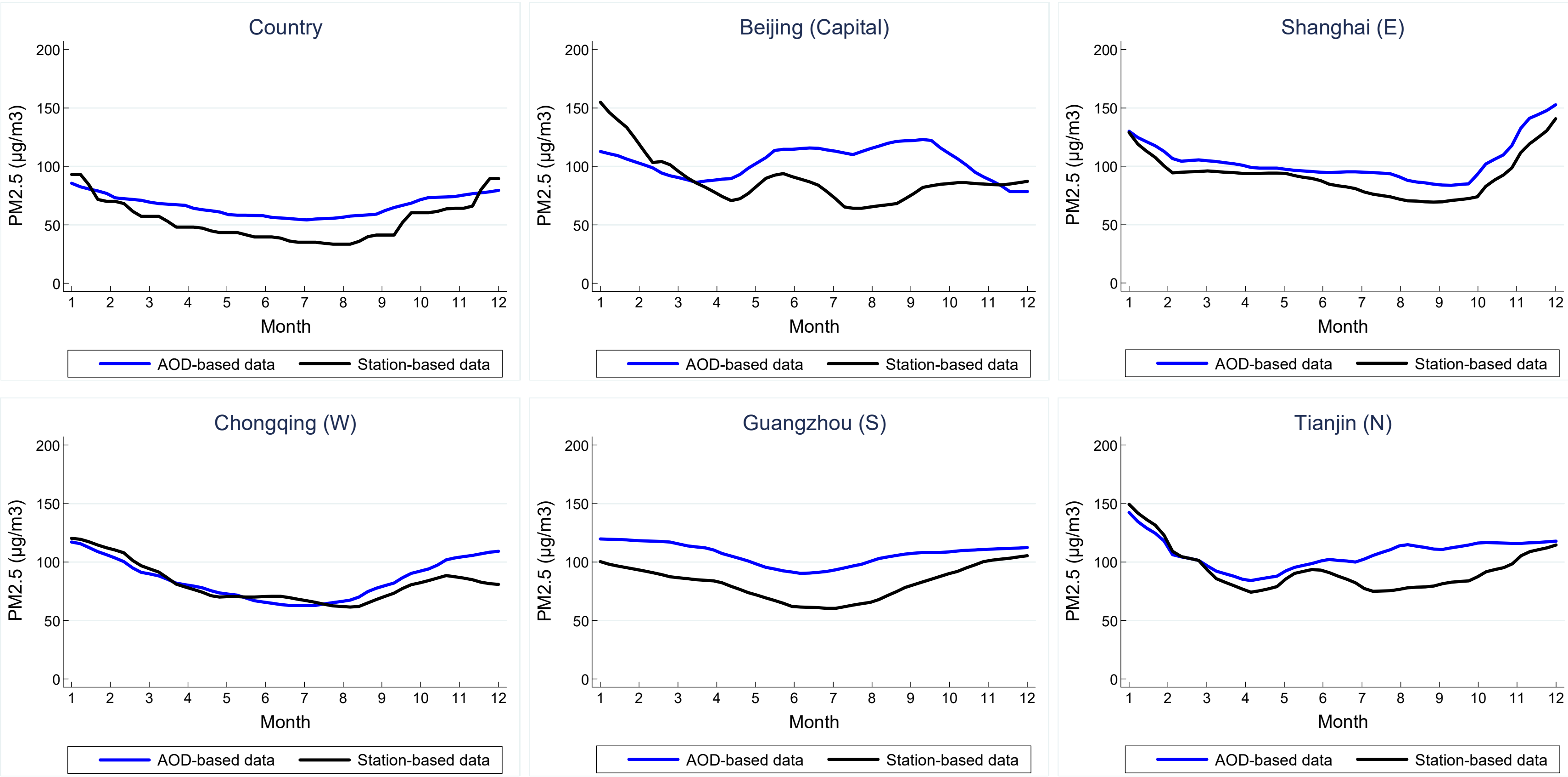


Figure A4: Monthly Trend between AOD-based and Ground-based PM2.5

Notes: This figure plots monthly trend between AOD-based and ground-based PM2.5 for the country and major cities.

Table A1: The Effect of $PM_{2.5}$ on Death Rates

	Years	All ages	Age below 15	Age between 15-60	Age above 60
		(1)	(2)	(3)	(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	187.0	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. 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 the contemporaneous year and the past 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 time window. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A2: Spatial Lag Model

	Net outmigration ratio				Immigration ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{2.5}$	0.6095***	0.4559***	0.6095***	0.4559**	-0.2499***	-0.3298***	-0.2499**	-0.3298**
	(0.1770)	(0.1722)	(0.2106)	(0.2094)	(0.0662)	(0.0867)	(0.1011)	(0.1467)
Net out. SL	0.5829	0.9029	0.5829	0.9029				
	(0.4494)	(0.6016)	(0.5279)	(0.6462)				
Immig. SL					0.1903	-0.0007	0.1903	-0.0007
					(0.2879)	(0.3598)	(0.4493)	(0.5233)
Observations	7,911	7,911	7,911	7,911	7,911	7,911	7,911	7,911
Number of counties	2,637	2,637	2,637	2,637	2,637	2,637	2,637	2,637
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weight	No	Pop in 1995	No	Pop in 1995	No	Pop in 1995	No	Pop in 1995
IV	Strength	Strength	Strength	Strength	Strength	Strength	Strength	Strength
Cluster	County	County	Prefect	Prefect	County	County	Prefect	Prefect
KP *F*-statistics	106.3	128.5	29.52	36.12	105.6	127.8	29.43	35.95

Notes: The dependent variables are net outmigration ratio in columns (1) – (4), and immigration ratio in columns (5) – (8). The spatial lag controls (net outmigration ratio spatial lag (Net out. SL) or immigration ratio spatial lag (Immig. SL)) are created with inverse distance weighting of migration flows in neighboring counties based on their centroid. The spatial lag controls and the pollution variables are instrumented using the thermal inversion strengths in the own county and the spatial lag of the thermal inversions respectively. Regression models are weighted using population aged 15 to 60 in 1995 in columns (2), (4), (6), and (8). The standard errors are clustered at either the county level (columns (1), (2), (5), and (6)) or prefecture level (columns (3), (4), (7), and (8)). Standard errors are listed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A3: Spatial Lag Model - First stage

	$PM_{2.5}$		Net out. SL		Immig. SL	
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal inversions	78.5956***	78.5968***	1.6561***	1.6562***	-1.0666***	-1.0666***
	(5.4767)	(13.2634)	(0.4419)	(0.5716)	(0.2540)	(0.3258)
Thermal inversions SL	237.2689***	237.2458***	-348.9912***	-348.9934***	292.2409***	292.2418***
	(68.8841)	(87.7809)	(10.4501)	(65.8131)	(5.2389)	(36.8083)
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	No	No	No	No	No	No
IV	Strength	Strength	Strength	Strength	Strength	Strength
Cluster	County	Spatial HAC	County	Spatial HAC	County	Spatial HAC

Notes: The dependent variable is $PM_{2.5}$ in columns (1) and (2), net outmigration ratio spatial lag (Net out. SL) in columns (3) and (4), and immigration ratio (Immig. SL) in columns (5) and (6). The spatial lag of thermal inversions (Thermal inversions SL), is created with inverse distance weighting of thermal inversions in neighboring counties based on their centroid. These regressions have standard errors clustered at either the county level (columns (1), (3), and (5)) or spatial HAC (columns (2), (4), and (6)). Standard errors are listed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A4: Spatial Lag Model - Reduced Form

	Net outmigration ratio			Immigration ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Thermal inversions	46.9302***	46.9621***	46.9653***	-19.8541***	-19.8514***	-19.8526*
	(13.1168)	(12.7663)	(16.3835)	(5.2313)	(5.3629)	(11.5344)
Thermal inversions SL		-47.5115	-47.5720		-3.9889	-3.9669
		(150.6978)	(166.9888)		(84.4155)	(99.6896)
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
Weight	No	No	No	No	No	No
IV	Strength	Strength	Strength	Strength	Strength	Strength
Cluster	County	County	Spatial HAC	County	County	Spatial HAC

Notes: The dependent variables are net outmigration ratio in columns (1) – (3), and immigration ratio in columns (4) –(6). The spatial lag of thermal inversions (Thermal inversions SL), is created with inverse distance weighting of thermal inversions in neighboring counties based on their centroid. These regressions have standard errors clustered at either the county level (columns (1) (2), (4), and (5)) or spatial HAC (columns (3) and (6)). Standard errors are listed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table A5: The Effect of Air Pollution on Immigration Ratio: By Occupation

	All occupations	Government/party /enterprise leader	Professionals	Clerks	Business/service	Agriculture	Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total immigration							
$PM_{2.5}$	-0.4080***	-0.6566***	-0.5041***	-0.4939***	-0.9402***	-0.1497**	-0.7675***
	(0.0975)	(0.1461)	(0.1158)	(0.1116)	(0.1299)	(0.0584)	(0.1103)
Mean [SD] of D.V.	7.32 [10.97]	11.49 [15.49]	9.46 [12.85]	9.10 [13.07]	15.08 [16.99]	2.78 [8.02]	11.56 [15.39]
Panel B: Within-province immigration							
$PM_{2.5}$	-0.3568***	-0.5940***	-0.4341***	-0.4224***	-0.7451***	-0.0684*	-0.6993***
	(0.0687)	(0.1278)	(0.1020)	(0.0980)	(0.1033)	(0.0380)	(0.0750)
Mean [SD] of D.V.	4.83 [7.24]	9.05 [12.82]	7.90 [11.11]	7.79 [11.39]	10.19 [12.42]	1.79 [5.69]	7.36 [10.26]
Panel C: Across-province immigration							
$PM_{2.5}$	-0.0511	-0.0626	-0.0700**	-0.0715*	-0.1951***	-0.0813**	-0.0682
	(0.0468)	(0.0498)	(0.0325)	(0.0368)	(0.0592)	(0.0395)	(0.0663)
Mean [SD] of D.V.	2.49 [5.71]	2.44 [5.82]	1.56 [3.77]	1.31 [3.93]	4.89 [8.88]	0.99 [4.41]	4.20 [8.59]
Observations	7,889	7,319	7,776	7,583	7,782	7,811	7,882
Number of counties	2,637	2,616	2,634	2,623	2,629	2,637	2,636
KP *F*-statistic	245.8	240.2	245.2	245.8	245.6	241.7	245.8

Notes: The dependent variable is immigration ratio, which is defined as the percent of population aged 15 to 60 entering the county with their *hukou* in the origin. Panel A includes total immigration, and Panels B and C include within-province and across-province immigration respectively. Column (1) includes all occupations. Columns (2) – (7) include each occupation. See detailed description of each occupation at http://ms.nvq.net.cn/nvqdbApp/htm/fenlei/index.html. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and weather controls. Regression models are weighted using population aged 15-60 for each group in 1995. Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A6: The Effect of Air Pollution on Migration: By Cities with and without API Data

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Net outmigration ratio for cities with API data						
$PM_{2.5}$	0.5314***	1.0016	1.0368***	0.6605***	0.6422***	0.6003***
	(0.1660)	(3.7282)	(0.3567)	(0.1421)	(0.1423)	(0.1539)
Mean [SD] of D. V.	-9.17 [16.15]	-11.99 [19.68]	-11.17 [18.44]	-9.87 [18.14]	-9.75 [18.21]	-9.77 [18.00]
Mean [SD] of $PM_{2.5}$	53.08 [27.93]	62 [26.61]	63.09 [25.76]	60.91 [26.35]	61.22 [26.30]	60.84 [26.16]
Panel B: Immigration ratio for cities with API data						
$PM_{2.5}$	-0.3246**	-1.0564	-0.4114*	-0.5227***	-0.5133***	-0.5168***
	(0.1329)	(4.7084)	(0.2100)	(0.1784)	(0.1773)	(0.1859)
Mean [SD] of D. V.	6.01 [10.73]	14.25 [17.90]	11.85 [16.36]	10.65 [15.67]	10.51 [15.58]	10.53 [15.57]
Mean [SD] of $PM_{2.5}$	53.08 [27.93]	62 [26.61]	63.09 [25.76]	60.91 [26.35]	61.22 [26.30]	60.84 [26.16]
KP *F*-statistic	250.7	20.03	43.15	81.28	64.64	81.65
Observations	7,911	1,326	1,956	2,193	2,232	2,238
Number of counties	2,637	442	652	731	744	746
Number of cities	**336**	**47**	**72**	**84**	**85**	**86**
Panel C: Net outmigration ratio for cities without API data						
$PM_{2.5}$	0.5314***	0.3297**	0.3468**	0.3253**	0.3392**	0.3220**
	(0.1660)	(0.1682)	(0.1661)	(0.1590)	(0.1653)	(0.1446)
Mean [SD] of D. V.	-9.17 [16.15]	-8.6 [15.28]	-8.51 [15.27]	-8.90 [15.32]	-8.94 [15.27]	-8.93 [15.36]
Mean [SD] of $PM_{2.5}$	53.08 [27.93]	51.28 [27.84]	49.79 [27.83]	50.08 [27.94]	49.88 [27.90]	50.02 [28.01]
Panel D: Immigration ratio for cities without API data						
$PM_{2.5}$	-0.3246**	-0.1977**	-0.2342**	-0.2382***	-0.2351***	-0.2420***
	(0.1329)	(0.0819)	(0.0940)	(0.0843)	(0.0851)	(0.0845)
Mean [SD] of D. V.	6.01 [10.73]	4.35 [7.57]	4.09 [7.08]	4.23 [7.32]	4.24 [7.34]	4.22 [7.33]
Mean [SD] of $PM_{2.5}$	53.08 [27.93]	51.28 [27.84]	49.79 [27.83]	50.08 [27.94]	49.88 [27.90]	50.02 [28.01]
KP *F*-statistic	250.7	206.8	182.6	167.8	53.74	172.3
Observations	7,911	6,585	5,955	5,718	5,679	5,673
Number of counties	2,637	2,195	1,985	1,906	1,893	1,891
Number of cities	**336**	**289**	**264**	**252**	**251**	**250**

Notes: This table reports the effect of air pollution on migration for cities with API data (Panels A and B) and for cities without API data (Panels C and D). Dependent variables are net outmigration ratio in Panels A and C and immigration ratio in Panels B and C. Column (1) is the baseline model which includes all cities. Since 2000, 47 cities have publicly available API data. Column (2) of Panels A and B include these 47 cities, and column (2) of Panels C and D include the remaining 289 cities. The number of cities with API data are increased after 2000. Therefore, the number of cities in columns (3) – (6) are increased in Panels A and B. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and weather controls. 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 A7: The Effect of Inversions on SO_2 (First Stage)

	(1)	(2)
Thermal inversions	24.9499***	28.2183***
	(2.3596)	(2.4171)
KP *F*-statistics	399.2	444.6
Observations	7,911	7,911
County FE	Yes	Yes
Period FE	Yes	Yes
Weather controls	Yes	Yes
Weighting	No	Yes

Notes: The dependent variable is SO_2. Regression models are estimated using Equation (2) and include county fixed effects, period fixed effects, and weather controls. Regression models are weighted using population aged 15 to 60 in 1995 in column (2). Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A8: The Effect of SO_2 on Migration

	FE	IV		FE	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Net Outmigration Ratio						
	No death adjustment			Death adjustment		
SO_2	0.8243***	1.8285***	1.5000***	0.8439***	1.8749***	1.5444***
	(0.1204)	(0.5268)	(0.5068)	(0.1213)	(0.5332)	(0.5121)
KP *F*-statistics	----	111.1	135.4	----	111.1	135.4
Panel B: Destination-based Immigration Ratio						
SO_2	0.3603***	-0.7936***	-0.9435***	----	----	----
	(0.0675)	(0.2215)	(0.2487)	----	----	----
KP *F*-statistics	----	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 variables are net outmigration ratio in Panel A and immigration ratio in Panel B. Through columns (1) – (3), 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 (4) – (6), net outmigration ratio is defined as the percent of population aged 15 to 60 leaving the county net of new arrivals and death. The immigration ratio is defined as the percent of population aged 15 to 60 entering the county with their *hukou* in the origin. Columns (1) and (4) are fixed effects models, and columns (2) – (3) and (5) – (6) are IV models. Regression models are weighted using population aged 15 to 60 in 1995 in columns (1), (3), (4), and (6). Standard errors are listed in parentheses and clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.

Table A9: 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
SW *F*-$PM_{2.5}$	104.02	----	104.02	----
SW *F*-SO_2	83.51	----	83.51	----
p-value of joint sig.	0.0003	----	0.0008	----
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
Mean [SD] of $PM_{2.5}$	----	53.51 [27.69]	----	----
Mean [SD] of SO_2	----	15.49 [11.87]	----	----
Mean [SD] of AQI	----	71.93 [35.95]	----	----

Notes: The dependent variables are net outmigration ratio in columns (1) and (2), and 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. 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. 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 A10: The Effect of Air Pollution on Firm Migration

	(1) Total	(2) State-owned	(3) Private	(4) Foreign	(5) Hybrid
Panel A: Outmigration ratio (%)					
$PM_{2.5}$	0.0612	0.3035	-0.1794	-0.0402	0.1361
	(0.2218)	(0.2646)	(0.2778)	(0.2956)	(0.4690)
Observations	4,972	4,350	4,480	3,296	3,916
Number of counties	2,486	2,175	2,240	1,648	1,958
KP *F*-statistics	59.43	64.06	78.85	53.70	63.25
Mean [SD] of Dep. Var.	2.01 [8.27]	2.03 [9.83]	1.77 [10.48]	2.74 [10.86]	2.18 [14.91]
Panel B: Immigration ratio (%)					
$PM_{2.5}$	-0.3384	0.1861	0.2225	0.4398	-0.6094
	(0.2755)	(0.3404)	(0.2431)	(0.3847)	(0.4101)
Observations	4,972	4,350	4,480	3,296	3,916
Number of counties	2,486	2,175	2,240	1,648	1,958
KP *F*-statistics	59.43	64.06	78.85	53.70	63.25
Mean [SD] of Dep. Var.	2.21 [8.08]	2.53 [9.81]	1.84 [9.48]	2.61 [10.01]	2.21 [8.98]
Panel C: Net outmigration ratio (%)					
$PM_{2.5}$	0.3996	0.1174	-0.4018	-0.4800	0.7456
	(0.3401)	(0.3598)	(0.3448)	(0.4966)	(0.6462)
Observations	4,972	4,350	4,480	3,296	3,916
Number of counties	2,486	2,175	2,240	1,648	1,958
KP *F*-statistics	59.43	64.06	78.85	53.70	63.25
Mean [SD] of Dep. Var.	-0.20 [9.65]	-0.50 [12.22]	-0.07 [12.97]	0.13 [12.78]	-0.22 [16.15]
County FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is county-period. The firm data are from the Chinese Industrial Enterprises Database, which covers all stated-owned and non-state firms with sales above CNY 5 million from 1998 to 2007. We define 1998-2002 as the first period, and 2003-2007 as the second period. The dependent variable in Panel A is the ratio between number of firms moving out from a county and number of total firms in that county in each period. The dependent variable in Panel B is the ratio between number of firms moving into a county and number of total firms in that county in each period. The dependent variable in Panel C is the ratio between number of firms moving out net of firms moving in and number of total firms in that county in each period. Regression models are estimated using Equation (1) and include county fixed effects, period fixed effects, and weather controls. Standard errors are listed in parentheses and clustered at county level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A11: Statistical Test Between AOD-based and Ground-based Pollution Data

	(1) Station	(2) AOD	(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)
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)
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)
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)
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 but vary across radii for the interpolation. Standard deviations are listed in parentheses in columns (1) and (2) and standard errors are listed in parentheses through columns (3) – (7) and are clustered at county level. * p <0.10, ** p <0.05, *** p <0.01.