The Mortality Impact of Fine Particulate Matter in China

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Abstract

We use county-level panel data on mortality to estimate the effect of fine particulate matter ($PM_{2.5}$) pollution on mortality in China. Causal inference relies on changes in local pollution correlated with demand shocks from export destinations amid the 2008 global financial crisis. Combining satellite data on local emissions with regional mortality data, we find an economically and statistically significant impact of the long-term exposure to $PM_{2.5}$ on cardiovascular and respiratory mortality. Mortality impacts are largest for those 65 years and older. Using the variability in particulate levels both across time and geographic space, we examine how the dose-response function changes at higher levels of pollution. We find evidence of a concave dose-response, with diminishing marginal mortality impacts of pollution at levels beyond those in developed nations.

Key words: $PM_{2.5}$, mortality, nonlinearity

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1. Introduction

Outdoor air pollution is one of the leading environmental factors for mortality, accounting for about 4.5 million premature worldwide deaths per year as of 2015. In the past decade, a body of economic studies examined the causal impact of air pollution on health, exploring exogenous variations in air pollution through quasi-experimental approaches (e.g., Beatty and Shimshack, 2014; Chay and Greenstone, 2003; Chay et al., 2003; Currie and Walker, 2011; Evans and Smith, 2006; Janke et al., 2009; Janke, 2014; Knittel et al., 2016; Schlenker and Walker, 2015). Most of these studies focus on areas with comparatively low levels of air pollution (e.g., OECD countries), where annual average $PM_{2.5}$ concentrations rarely exceed 30 micrograms per cubic meter of air (μg/m^3) (Pope and Dockery, 2013).[2] In major developing and fast-growing countries such as China and India, $PM_{2.5}$ concentration is much higher, and half of premature pollution deaths occur in China and India (Lancet Commission, 2016). During the 2011-2015 period, while less than 20% of the population in OECD and high-income countries were exposed to $PM_{2.5}$ with the annual mean concentration above the WHO guideline of 10 μg/m^3, more than 90% of the population in low-and-middle income countries faced such levels. For example, the annual concentration of $PM_{2.5}$ in China was constantly over 50 μg/m^3 in recent years.[3]

The relationship between economic growth and environmental quality presents a challenge to developing economies. Income growth increases the demand for environmental quality and quality of life. At the same time, the rise in vehicle ownership and travel demand, together with the burning of fossil fuel for industrial activities to maintain economic growth, continue to put pressure on the environment. Understanding the potential tradeoff between economic growth and environmental quality requires a better understanding of the health impact of environmental quality in developing economies. As

[2] $PM_{2.5}$ or fine particulate matter refers to particulate matter of less than 2.5 micrometers in aerodynamic diameter.

[3] China's $PM_{2.5}$ concentration in 2014 was more than six times of that in the US (8μg/m^3) in the same year (WHO, 2016), almost three times of that (21μg/m^3) during the period of 1979-1983 (Pope et al., 2009) and almost twice of that (30μg/m^3) in the most polluted United States cities in the late 1970s. China's $PM_{2.5}$ concentration in 2014 was ranked in the 169th place among all 184 countries that have data available and twice of the world average (26 μg/m3) in 2014 (WHO, 2016). Population weighted annual concentration of $PM_{2.5}$ in China in 2010 (mean 59μg/m^3) substantially exceed levels in India (28μg/m^3) (Apte. et al., 2015). The annual standard set by China's Ministry of Environmental Protection (MEP) is 35 μg/m^3.

economic growth is often accompanied by improvement in health care, establishing a causal link between air pollution and health is particularly complicated in rapidly developing nations. As a result, the exact regions that stand to benefit most from understanding the link between air pollution and health are those with traits that could complicate identifying causal associations.

This paper examines the causal impact of long-term exposure to $PM_{2.5}$ on mortality in China, using county-level panel data for the 161 counties covered by the Disease Surveillance Point System (DSPS) of Chinese Center for Disease Control and Prevention (CDC) for the periods of 2004, 2008, and 2010. To address the potential endogeneity of $PM_{2.5}$ concentration, we construct an instrumental variable (IV) leveraging the 2008 worldwide economic recession, which generates plausibly exogenous shocks to export demand and hence local manufacturing activities in different parts of China. Our IV is the interaction between two factors that vary at the local level: (1) pre-sample (year 2000) export intensity at the county level, and (2) the total exports to top 5 importing destinations at the county level. Such shocks affect counties in China differently because of cross-county differences in exposure. Our causal inference relies on county-level $PM_{2.5}$ variation from demand shocks in corresponding exporting destinations in the spirit of Autor et al. (2013), which leverages supply-driven shocks in China to measure the impact of trade on the U.S. labor market. Economic shocks to export destinations propagate through demand for goods from different counties in China, leading to variations in local manufacturing activities and thus $PM_{2.5}$ concentrations.

We find long-term exposure to $PM_{2.5}$, as measured by three-year ambient pollution levels, causes a significant increase in all-cause and cardiorespiratory mortality. $PM_{2.5}$ has the largest mortality impact on those 65 years and older; this has strong implications for the future disease burden given a growing older population in China. Using the substantial variation in $PM_{2.5}$ both across time and location, we also examine how the dose-response pollution and health function changes at higher and lower levels of emissions. We find suggestive evidence of larger marginal mortality impacts at lower concentrations, indicating the dose-response function is concave. This aligns with the important recent findings in

Cohen et al (2016) that air quality improvements will result in only "modest reductions in burden in the most polluted countries unless PM2.5 concentrations decline markedly."

Our results align with the growing body of economics literature on estimating the impact of air pollution on mortality in economics. Much of this literature pays particular attention to causal inference by leveraging potentially exogenous variation in air pollution. While earlier work focused on infants (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Knittel et al., 2015), recent research shows negative effects for adults as well (Anderson, 2015; Barreca, Neidell, and Sanders, 2018; Deryugina et al., 2018). We provide empirical evidence on the health impact for the older population under much higher levels of air pollution than those observed in aforementioned studies. Our estimation is most closely related to Chen et al. (2013), He et al. (2016) and Ebenstein et al. (2017), all of which consider the relationship between pollution and mortality in China. Our results are broadly consistent earlier findings, while providing three important additions. First, Chen et al. (2013) estimate the impact of TSP and He at al. (2016) and Ebenstein et al. (2017) examine PM_{10}, while our analysis focuses on $PM_{2.5}$. Health literature suggests fine particle $PM_{2.5}$ (including sulfates, nitrates, acids, metals, and particles with various chemicals adsorbed) has larger adverse health impact because they may be more toxic and can penetrate deeper into lungs and remain suspended for longer period of time than larger particles such as PM_{10} (Pope and Dockery, 2012). Second, Chen et al. (2013) and Ebenstein et al. (2017) use the regression discontinuity approach based on the Huai river heating policy in China. We offer a different identification strategy using variation across both location and time. Our results largely align despite using two very different identification strategies, which supports earlier findings. Third, our analysis examines the shape of the dose-response function by considering effects above and below the median $PM_{2.5}$ levels in China (42 $\mu g/m^3$).

Section 2 of this paper provides background on China’s air pollution challenge and describes various data components. Section 3 provides graphic evidence to illustrate the identification strategy. Section 4 discusses our empirical framework. Section 5 presents empirical results, and Section 6 concludes.

2. Background and Data

2.1 Background

Amid heightened public concerns of health impacts of air pollution, improving air quality has become a major policy goal of the Chinese central government. Every five years, China's Central Government issues a new Five-Year Plan (FYP), outlining the country's socio-economic development goals for the next five years. China's 11th FYP (2006-2010) first proposed monitoring $PM_{2.5}$ in major cities in China. The 13th FYP (2016-2020) explicitly regulated $PM_{2.5}$ pollution as a key policy goal.[4] Economic development remains the most important focus of local and national governments, and these FYPs also set forth the specific strategies to achieve development goals.

Recent national plans such as the One-Belt and One-Road initiative aim to reduce economic disparity across different regions by encouraging manufacturing activities to move from the east coast to the west and by improving public infrastructure and investment in the western region. These economic development strategies could lead to significant changes in environmental quality in an area where environmental awareness among the general population may be weak and access to healthcare is still poor. The potential tradeoff between economic development and environmental quality should be an important concern for policy makers (Grossman and Krueger 1995), and understanding the health consequence of environmental degradation such as air pollution is an important component in that tradeoff.

2.2 Data and Descriptive Statistics

We assemble several data components on mortality, air pollution, trade, and socioeconomic conditions at the county level from multiple sources covering the years 2004, 2008, and 2010. Our data vary at either the prefecture or county level, where prefecture is a higher level of aggregation and contains multiple counties.

[4] FYPs are passed by the Standing Committee of National People's Congress, the highest-level of government organ that has the power to legislate. The first FYP was made for the period of 1953-1957.

Mortality data

Mortality data are from the Disease Surveillance Point System (DSPS) of the Chinese Center for Disease Control and Prevention (CDC)[5]. We obtained confidential mortality statistics by age group, gender, and by cause of deaths for all 161 counties/city districts covered by DSPS for 2004, 2008 and 2010. The data divide population into six age groups: (0-15 years), [15-20 years), [20-35 years), [35-50 years), [50-65 years), and 65 years and above. Causes of mortality fall into four categories: respiratory, cardiovascular, suicide, and other. For our analyses, we group populations in a given county into three age groups, including children and teens (below 20 years), young and middle-aged (between 20 and 65 years) and the elderly (65 and above).

The raw mortality rate counts the total number of deaths divided by the midyear population. As many health outcomes vary by age, to compare groups with different age distributions, we construct the age-adjusted mortality rate. Based on the raw mortality rate data, we calculate the age-adjusted mortality rate for each age group for a given county. In county *i*, there are *k* (k=1,..., K) age groups, the population size of age group *k* is N_{ik} and the total mortality in age group *k* is N_{ik}. $M_{ik} = \frac{d_{ik}}{N_{ik}}$ is the age-specific raw mortality rate for age group k in county *i*. The age-adjusted mortality is defined as

$$= \sum_k w_k M_{ik} \ ,$$

where w_k is the reference population share by age in China.

Pollution data

We focus on long-term exposure to $PM_{2.5}$ on mortality. In epidemiology, long-term exposure often refers to exposures of a year or more to ambient air pollution (e.g., Pope et al., 2002; Brunekreef et al., 2006; Hoek et al., 2013; Miller, 2013). We measure pollution exposure using $PM_{2.5}$ concentration derived from satellite Aerosol Optical Depth

[5] For detailed discussions on the establishment of surveillance points set by CDC and mortality information, please be kind to refer to Zhou et al. (2015).

observations.[6] In China, ground-level air quality monitoring stations before 2013 were rare and the information was not public. We retrieve data from the Global Annual $PM_{2.5}$ Grids from MODIS (Moderate Resolution Imaging Spectroradiometer), MISR (Multi-angle Imaging SpectroRadiometer), and SeaWiFS (Sea-Viewing Wide Field-of-View Sensor) Aerosol Optical Depth (AOD) data sets, which have been used in many health impact studies (e.g. Brauer et al., 2012). These data sets are a series of three-year running averages of fine particulate matter at the grid level derived from a combination of MODIS, MISR and SeaWIFS AOD satellite retrievals during 1998-2012. Grids have a resolution of 0.1 x 0.1 degrees. We transform satellite-derived $PM_{2.5}$ data at the grid level to 161 counties/city districts using geographic information (the longitude and the latitude) of each county. We use the current year and past two-year average $PM_{2.5}$ concentration for 2004, 2008 and 2010 as the long-term exposure to $PM_{2.5}$ and hereafter refer to this value as our measure of $PM_{2.5}$ concentration.[7]

Trade data

We collect information on the export of industrial goods and their destination countries for 145 prefectures covering our 161 county/city districts from China's Customs database. We identify the top five destination countries for each prefecture during the period of 2001-2010, then collect information on total imports of these countries from China in each year from the World Bank's World Development Indicators. For each of 161 counties/city districts, we construct a measure of export intensity (total export/total GDP from the manufacturing sector) in 2000. This variable captures the susceptibility of the local (county) economy to economic shocks of exporting destinations. Our instrument is the interaction between the baseline (year 2000) export intensity of each county and total exports from China to each county's top 5 destination countries. The interaction allows demand shocks from the same destination countries to have different effects across Chinese counties depending on county trade intensity.

[6] The data is available from http://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-avg-pm2-5-2001-2010. Satellite remote sensing data are being increasingly used for air quality measurement due to its extensive spatial coverage (Li et al. 2015).
[7] For example, the pollution level reported for 2004 is an average of pollution levels in 2002, 2003, and 2004.

Socio-economic data

Socioeconomic conditions at the local level can affect both pollution and health outcomes. In the Chinese context, prefectures are the hubs of local economic development as well as healthcare services. Residents in counties usually go to hospitals in the capital city of the prefecture when they have a severe illness, some of which may not be treatable by local hospitals at the county seats. This presents a spatial complication, as neighboring counties in the same prefecture may benefit from government spending on health care and pollution reduction as well as hospital facilities provided at the prefectural level.

Given the above context, instead of collecting county-level socio-economic information, we collect prefectural-level data from Statistical Yearbooks of Prefectural Cities in China (2001-2010). Variables include: GDP per capita, local government spending, number of employees, and total number of hospital beds. We generate the past 3-year average for each variable for 2004, 2008, and 2010 to be consistent with the timing of our $PM_{2.5}$ exposure variable.

Weather data

We collect daily weather information from the National Bureau of Meteorology on temperature, precipitation, humidity, solar radiation and wind speed for each station, and then aggregate daily information. Considering weather conditions may have non-linear effects on pollution and health outcomes (see, for example, Barreca et. al 2016), we create temperature bins with a bandwidth of 10-degree days in Fahrenheit at the station level. Among those 161 counties covered by the DSPS system, some counties have weather stations while others do not. For counties without weather stations, we use Inverse Distance Weighting (IDW) interpolation to generate a county-level measure. Specifically, for a given county/city district, we take the weighted average of weather data from stations within a radius of 200 km using the IDW method. As with other variables, we calculate the past 3-year average values to be consistent with the timeframe of the pollution variable.

2.3 Summary statistics

Table 1 presents summary statistics for all variables used in our study. Across 2004, 2008 and 2010, the average annual age-adjusted total mortality rate was 105 deaths per 100,000 people. The average age-adjusted respiratory and cardiovascular mortality rates were 57 and 42 deaths per 100,000 people, respectively.[8]

The aggregated 3-year $PM_{2.5}$ concentration for the 161 counties was 44.14 μg/m^3 (first row of the Table 1) and the population weighted average annual $PM_{2.5}$ concentration was 45.73 μg/m^3 (second row of the Table 1), which is substantially higher than the WHO guideline for $PM_{2.5}$ average annual exposure (10 μg/m^3) and the US EPA's primary standard (12 μg/m^3). It was also higher than China's national standard (35 μg/m^3). These 161 counties, on average, have better air quality than the national average; counties in the country's most polluted areas (such as Hebei, Henan, Shandong and Shanxi) are under-sampled. The average $PM_{2.5}$ concentration at the national level based on over 1000 ground level monitoring stations was 56 μg/m^3 during 2013-2015 and the population weighted average was 62 μg/m^3.

Table 1 also shows large variations, ranging from 1 μg/m^3 to 117 μg/m^3, among counties in terms of regular exposure to $PM_{2.5}$ pollution. Counties' median $PM_{2.5}$ concentration was 42 μg/m^3. Figure 1 depicts variation in the exposure to $PM_{2.5}$ pollution across counties in 2010, showing substantial geographic variation in levels. Most counties in central and eastern China had $PM_{2.5}$ concentration levels higher than China's national standard, while counties in land-locked western China and remote regions in northeastern China have comparatively lower $PM_{2.5}$ concentrations (below 19 μg/m^3).

Figure 2 presents variation among sample counties in terms of *changes* in the exposure to $PM_{2.5}$ pollution from 2004 to 2010. Most counties experienced an increase in $PM_{2.5}$ concentration between 2004 and 2010, but with varied magnitudes of change across counties. Some counties experienced changes greater than 20 μg/ m^3 while others saw changes below 1 μg/ m^3. Counties experiencing the biggest change are located in central

[8] The average age-adjusted mortality rate due to suicide was about 1.68 deaths per 100,000 people per year.

and eastern China, while counties with smaller changes are from land-locked western China and the more remote part of northeastern China.

2.4 Variations in $PM_{2.5}$, Mortality and Trade

The timing of our available mortality data spans the global financial crisis in 2008, which significantly affected international trade between China and its major trading partners. Between January and February of 2009, China's overall exports were 17.5% lower than the corresponding months in 2008 (Whalley et al., 2009). The annual changes in exports of goods/services in 2008 and 2009 were -1% and -12%, respectively. With the reduced demand for China's output from destination countries, production of industrial goods likely contracted, driving changes in $PM_{2.5}$ concentrations. Figure 3 shows trends in average $PM_{2.5}$ concentrations, the mortality rate, top-5 destination country imports from China (the basis for our instrument and averaged from the county level), and GDP per capita during 2004, 2008, and 2010.[9]

Between 2004 and 2010, GDP per capita increased steadily, which implies local GDP growth is not driven entirely by trade. Although $PM_{2.5}$ concentration and top-5 imports from China increased overall from 2004 to 2010, both peaked in 2008 and then decreased slightly by 2010. All-cause mortality reached its lowest level in 2008, ending slightly higher in 2010 but still below initial 2004 levels. Figure 3 thus provides suggestive evidence on [1] the possible co-movements of $PM_{2.5}$ concentration and top-5 imports from China during our period, and [2] a close relationship between changes in $PM_{2.5}$ concentration and changes in mortality.

The increasing trend of $PM_{2.5}$ concentration masks heterogenous changes in $PM_{2.5}$ concentration by county, due possibly to different industry structures and socio-economic characteristics. To investigate how our variables change over time for higher- versus lower-pollution areas, we take the change in $PM_{2.5}$ concentration between 2004 and 2010, calculate change quartiles, and then divide all counties into three groups: groups with little

[9] We identify top-5 destination countries for each county according to detailed information of the export of industrial goods from the county and their destination countries. Once the top-5 destination countries are identified, we then compile information on their import from China for each year during our sample period.

pollution change (lowest quartile), medium (25^{th}-75^{th} percentile), and big (greatest quartile) pollution changes.[10] Note that, unlike trends in developed nations, pollution levels in China are generally *increasing* over time. As a result, each groups sees pollution increase overall across the period, but there is variation in the total size of the increase.

Figure 4 shows striking differences across groups in terms of changes in $PM_{2.5}$ concentration. In the "Big Change" group, $PM_{2.5}$ concentration increased by 38%, while the "Small Change" group had only a 3% increase during the same period. $PM_{2.5}$ concentrations in the "Big Change" group increased in both 2008 and 2010, while the "Small Change" and "Middle Change" groups, both reached peak $PM_{2.5}$ concentration in 2008.

Figure 5 plots the mortality rate by the same grouping. These are unadjusted mortality differences that contain a good deal of noise, so are suggestive at best. Unlike pollution levels, mortality rates are decreasing across time. This hints at a possible source and direction of bias in OLS estimate, where general trends in economic development (increasing) and mortality (decreasing) might bias results in the negative direction. Panel A shows the trend in all-cause mortality, while Panel B presents the trend in respiratory mortality.

The figure shows counties with the smallest increases in $PM_{2.5}$ concentration had the largest decline both in all-cause and respiratory mortality. In Panel A, all-cause mortality declined more for the "Big Change" group than the "Middle Change" group, though for respiratory mortality the "Big Change" group declined less rapidly than the "Middle Change" group. The different trends of these two categories of mortality may be because all-cause mortality also includes factors other than $PM_{2.5}$ pollution, while respiratory mortality has been shown to be closely associated with particulate air pollution (see Pope and Dockery, 1994).

Our IV identification hinges on the differential impacts of the 2008 financial crisis. Figure 6 provides visual inspections on changes in the top-5 destination imports from China

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[10] The big change group consists of counties with the biggest change (i.e. in the 75th percentile, with $PM_{2.5}$ concentration increased by 14.36 $\mu g/m^3$) and the small change group consists of counties with the smallest change (i.e. in the 25th percentile, with $PM_{2.5}$ concentration increased by 2.89 $\mu g/m^3$). The middle change group is composed of all other counties, i.e. 25th -75th inter-quartiles.

by counties across different $PM_{2.5}$ change groups and exhibits two salient features. First, for counties in all three groups, the top-5 imports from China all peaked in 2008 and had very similar rates of change over time. Second, during 2008 and 2010, changes in top-5 imports for counties in the "Big Change" group were larger than the other two groups. In terms of the size of export in 2000, counties in the "Big Change" group had the largest variation, while counties in the "Small Change" group had the smallest. These results suggest that the 2008 crisis had differential impacts across the sample counties depending on the composition of their destination countries.

3 The Empirical Framework

We estimate the following linear model to identify the mortality effect of $PM_{2.5}$ concentration:

$$y_{it} = pm_{it}\alpha + x_{it}\beta + \mu_t + \delta_i + \varepsilon_{it}, \quad (1)$$

where *i* denotes a county-age-gender cell and *t* denotes a year. y_{it} is the mortality rate for county-age-gender group *i* in year *t*. *pm* denotes the 3-year (*t*, *t-1*, and *t-2*) average of $PM_{2.5}$ concentration. x_{it} is a vector of control variables including weather conditions and socioeconomic variables. μ_t is a vector of year fixed effects, and δ_i a vector of county-age-gender fixed effects. We cluster standard errors at the county level, the level of variation for mortality and emissions data.

The key empirical challenge in identifying the impact of $PM_{2.5}$ on mortality is the potential endogeneity of $PM_{2.5}$ from measurement error and/or unobservables. Our $PM_{2.5}$ data are derived from the satellite data on Aerosol Optical Depth rather than from ground-level monitors[11]. Measurement errors arise when translating the satellite data to ground level $PM_{2.5}$ concentrations through a combination of estimation models and spatial extrapolation methods. To the extent measurement error uncorrelated with the true value, OLS estimates are subject to attenuation bias.

[11]Measurement error also exists when using ground monitoring station data, leading to attenuation bias. For detailed discussion, please refer to a recent paper by Jia et al. (2017).

Unobservables such as avoidance behavior and economic growth related to both the pollution level and health outcomes could be a second source of endogeneity. To reduce pollution exposure, individuals may decrease outdoor activities or choose to wear anti-smog facemasks or install indoor air purifiers. Recent studies in China find a strong and positive relationship between observable air pollution and the purchase of preventive products such as face masks and air purifiers (e.g. Zhang and Mu, 2014; Ito and Zhang, 2016 and Su et al., 2017). In addition, individuals may engage in short- or long-term migration to reduction pollution exposure. Although the rigid Hukou system in China may limit residential sorting, anecdotal evidence does show an increasing number of the elderly from regions where winter smog is heavy and weather is harsh, temporarily migrate to Hainan Province in southern China to spend their winter (Zhai et al., 2015). These different types of avoidance behavior could bias the mortality impact downwards.

Our IV strategy leverages demand shocks due to the 2008 global financial which generate variation in the demand for manufacturing goods and hence pollution across counties. We construct the IV by: [1] finding each county's top-5 exporting destination countries and generating the average import from China over the past three years (to align with the temporal resolution of our emissions data), and [2] interacting the average import with the pre-determined (year 2000) export intensity of the county measured by the total export of the prefectures where the country is located. The interaction term leverages both cross-sectional variation in export intensity and yearly variation in exports to allow demand shocks from the 2008 global financial crisis to have differential impacts across origin counties. The IV also leverages the temporal and cross-sectional variations in the demand shocks due to the variation in exporting destinations across counties.

The identifying assumption is that demand shocks in the top-5 exporting destinations of each county affect health outcomes of that county only through impacts on $PM_{2.5}$ levels. There are two concerns regarding the validity of the assumption. First, demand shocks from exporting destinations could affect local economic conditions which in turn could affect health outcomes. We control for a rich set of social and economic variables in our model such as GDP per capita, government spending, population density, hospital beds and employment. Our results show that, in both in the first and second stages, local socio-economic variables are not significant and controlling these variables does not change the coefficients of interest, implying those potential confounders are unlikely to be a threat to identification. Second, one might worry the economic downturn in destination countries could be affected by the exports in China given the importance of the China in the export market. Here we note the 2008 worldwide economic crisis was initially caused by the bust of the housing market bubble in the United States; China's economy was quite robust itself during the crisis and played a positive role in helping with world economic recovery.[12]

4 Empirical Results

5.1 Relation between $PM_{2.5}$ concentration and all-cause mortality

To analyze the pollution-health relationship, we follow the convention in the literature and use a log-linear functional form. The dependent variable is log-transformed mortality and the key regressor is the three-year average $PM_{2.5}$ concentration, which serves as a proxy for measuring long-term exposure to $PM_{2.5}$.

We start with OLS to analyze the association between $PM_{2.5}$ and all-cause mortality. The first model is a pooled cross-sectional OLS model including socio-economic and weather controls. The second model adds year fixed effects to control for common shocks in all counties over years, such as changes in macro-economic conditions and national health care policies. The third model adds county-age-gender fixed effects to control for unobserved time-invariant determinants of mortality. We next apply the IV with the same sets of controls.

Socio-economic controls are at the prefectural level, and include GDP per capita, population density, government spending, number of hospital beds and employment. Weather controls are at the county level and include bins of temperature, precipitation, wind speed and humidity. We weight all regressions by county age/gender population.

[12] For example, China surpassed the U.S. in new vehicle sales to become the largest automobile market in 2009. GM sold more cars in China than in the US for seven consecutive years since 2010 and the robust market in China helped pulling GM from the brink of the bankruptcy.

Table 2 presents regression results. OLS results in columns (1) - (3) show a positive but statistically insignificant relationship between the long-term exposure to $PM_{2.5}$ and all-cause mortality. A 10 $\mu g/m^3$ increase in $PM_{2.5}$ (approximately 40% of one standard deviation) raises mortality rates by 1-3%. IV results in columns (4)-(6) show a positive and statistically significant effect that is much larger: the full model estimate in column (6) is 0.022, almost 8 times as large as the corresponding OLS estimate in column 3, and statistically significant at the 1% level. This suggests a 10 $\mu g/m^3$ increase in the long-term exposure to $PM_{2.5}$ would lead to a 22% increase in all-cause mortality. The F-statistics on the IV from the first-stage shown in the last row of the Table 2 suggest our first-stage is strong enough by conventional measures for second-stage inference (full first-stage results are in Appendix Table 1).

The large difference between the OLS and 2SLS methods is common in recent economic literature using IV methods to identify the health effect of air pollution (e.g. Knittel et al., 2015; Schlenker and Walker, 2015).[13] But it is also possible our instrument impacts mortality through channels other than particulate matter. A common problem in single pollutant models is that the coefficient on the included pollutant carries all the mortality impacts from other correlated pollutants. For example, if $PM_{2.5}$ reductions go along with reductions in ozone, carbon monoxide, or other hazardous emissions, our model assigns gains from reduction in co-pollutants to $PM_{2.5}$ exclusively. It may be that our instrument impacts health through other channels our model does not include, which would similarly place the weight of such changes on the $PM_{2.5}$ coefficient. Columns (4) to (6) in Table 2 show that the coefficient estimates are quite robust across different model specifications where different sets of controls are included, which suggests that, at least within our model as specified, the instrument effects are not a result of a common non-pollution channel (e.g., income). Specifically, the difference between the coefficient estimate in the model without socio-economic controls (column 5) and that with those controls (column 6) is quite small (0.026 vs. 0.022).

[13] Attenuation bias alone likely cannot explain differences of this size – other relevant sources of bias include avoidance behavior and improvements in health care that go along with economic development.

To place the magnitude of our findings in context, we summarize comparable estimates of pollution and mortality in China from the economics literature. Most closely related is Ebenstein et al. (2017), which identifies the causal effect of long-term exposure to PM_{10} in Northern China using a regression discontinuity design to leverage the heating policy differences across the Huai River. The estimated coefficient from their study, an 8%-11% increase in mortality per 10 units of PM_{10}, is about one-third to one-half the size of our IV estimates. Chen et a. (2013) find a 10 $\mu g/m^3$ increase in total suspended particulates (TSP), which includes $PM_{2.5}$ and PM_{10}, increased mortality rates by 1.4%. Comparing these two results suggests the impact of PM_{10} is approximately 7 times that of TSP. We know of no direct conversion between the effects of a unit of TSP, PM_{10} and $PM_{2.5}$, though the health literature suggests the per-unit health effects increase as particle size decreases, which aligns with the above results. As a point of further comparison, Appendix Table 4 shows results from various other pollution and health studies in epidemiology and economics.

5.2. Heterogeneity of the health effect of long-term exposure to $PM_{2.5}$

Recent studies recognize the health impact of air pollution can differ across population groups with different characteristics such as age and gender (Schlenker and Walker, 2015; Clougherty, 2010; Zhou et al., 2016; Dockery and Pope, 1993). We first analyze effects by age groups in terms of all-cause mortality, cardiorespiratory mortality (i.e., mortality due to cardiovascular and respiratory) and respiratory mortality. The strong link between cardiorespiratory mortality and long-term exposure to $PM_{2.5}$ has been well-established in epidemiological studies (e.g. Pope et al., 1995, 2002, 2004; WHO, 2006). Studies have also shown that elderly people and children are particularly vulnerable to the exposure to pollution (WHO, 2013; Brook et al., 2012). In the epidemiological research, the link between PM pollution and respiratory mortality is among the first to be established (as reviewed by Dockery and Pope, 1993; Lim et al., 2012). For all subgroup analysis we focus on the IV results.

Table 3 shows the IV results by age groups (Appendix Table 2 shows first-stage results). Panels A and B show suggestive evidence health effects of $PM_{2.5}$ pollution vary across age groups. In all but one case (all-cause mortality for the below 20 age group) results are statistically significant at conventional levels. Coefficients across age groups are close enough to be statistically indistinguishable, though magnitudes are largest for the age 65 and above group in all cases.

To examine the robustness of the results, we run additional regressions using the linear-linear form. Table 4 presents the estimation results by age with the linear functional form. The elderly group remains most vulnerable group among all age groups, consistent with results from the log-linear specifications.

5.3 The shape of the dose-response function.

Discussions in the epidemiological literature suggest nonlinearity has important implications for public polices (e.g. Pope et al., 2009; Pope and Dockery, 2006). To address the lack of data and rigorous empirical evidence on the health impacts of air pollution in developing countries, the literature has often relied on the benefit transfer approach which interpolates the estimated dose-response function in developed countries to developing countries (e.g., Lelieveld et al. 2015 and World Bank 2007). However, the level of concentration in developing countries is often outside of the range observed in developed countries. Whether the dose-response function exhibits nonlinearity is critical for conducting credible out-of-sample predictions and understanding optimal levels of regulation.

An advantage of our study is the wide variation in pollution levels across time and space in China, which allows for greater study of the dose-response shape. To test for evidence of nonlinearity, we run linear spline regressions for all-cause, cardiorespiratory and respiratory mortality. Ideally, we would trace out the shape of the dose-response function across many levels. In our IV framework, each additional knot in the spline generates another potentially endogenous variable and thus requires an additional instrument for sufficient identification. This means we face a trade-off between statistical power and flexibility. We opt to test across two regions in the pollution distribution, using the median (42 $\mu g/m^3$) of the $PM_{2.5}$ concentration as the cut-off point for our linear spline regressions. This cut-off point is very close to the global annual median concentration of

$PM_{2.5}$ pollution in urban areas in 2014 (43 μg/m^3) (WHO, 2016) and annual mean concentration of $PM_{2.5}$ pollution in China in 2017 (43 μg/m^3).

To generate additional instruments, we create four dummy variables based on quartiles of $PM_{2.5}$ concentration (below the 25th percentile, between the 25th percentile and the 50th percentile, between the 50th percentile and the 75th percentile, and above the 75th percentile). We then interact these four dummy variables with the original IV and their square terms to generated eight IVs for spline regressions. Our intent is to not just increase the number of available instruments, but to do so in a manner that is consistent with identifying effects at different levels of the distribution of pollution. This instrument could potentially violate the exclusion restriction if the quartile of pollution levels correlates with the error term in the regression of pollution and mortality.

Columns (1)-(3) in Table 5 show marginal effects are statistically and economically significant for both higher and lower levels of pollution. For all-cause mortality, the marginal effect of the $PM_{2.5}$ pollution at the lower concentration level is 1.41 additional deaths per 100,000, which is approximately 50% higher than marginal effects at higher levels, 0.92 additional deaths per 100,000. These results are suggestive of a concave dose-response function, which support the recent results in Cohen et al. (2015).

The F-statistic for the first stage is weak for the below-median range (7.85), below the Stock-Yogo critical value. Further, standard errors are large enough such that, while both portions of the spline are statistically different from zero, they have overlap in their confidence intervals. Both factors suggest we should be cautious in interpretation of differences in marginal effects across the pollution distribution. Columns (2) and (3) show that we observe similar patterns for cardiorespiratory and respiratory mortality, where the marginal effect of the pollution at the lower level is 30% and 70%, respectively, higher than that at the higher level.

The diminishing marginal effect of pollution on health suggests the shape of the dose-response function is concave higher pollution levels. This suggests larger health benefits to reducing $PM_{2.5}$ below 42 μg/m^3, a level below the annual mean $PM_{2.5}$ concentration in China in 2017 and the global annual median concentration in urban areas in 2014. This also implies returns to improving air quality may appear low when pollution levels are very high, which carries important implications for comparing studies across low- vs. high-pollution areas. The concavity in the dose-response function means out-of-sample projections of health benefits from reducing $PM_{2.5}$ in developing countries based on the dose-response function at the low level of concentration typically observed in developed countries could lead to overestimation.

Variation in the shape of the dose-response function may also help explain why some successful pollution-reduction programs in high-pollution areas see limited marginal improvements in health. For example, Greenstone and Hanna (2014) find that a catalytic converter policy in India reduced ambient total suspended particulates by 49 $\mu g/m^3$, but observed only small and statistically noisy improvements in infant mortality (a reduction of 0.6 deaths per 1,000 live births).[14] They did not perform an IV analysis, but converting their reduced form result to an IV by dividing by the "first stage" gives a (noisy) marginal effect of 0.01 deaths per 1,000 live births per unit of particulates. This is at a very high pre-policy pollution level of 252 $\mu g/m^3$. Compare that to the Chay and Greenstone (2003) results from the United States which finds 0.05 fewer deaths per 1,000 live births per unit of particulates, from a pollution baseline of approximately 70 $\mu g/m^3$.[15] Our results suggest one reason for the small effect may be the concavity of the dose-response function, which suggests that reductions in particulates may have had small marginal effects, but also pushed India toward a point of higher marginal returns to further reductions.

5 Conclusion

Using mortality data by age groups and gender from 161 counties in China in 2004, 2008 and 2010, we estimate the causal impact of ambient $PM_{2.5}$ on mortality in the context of a modern developing economy. Our identification relies on variation in pollution induced by demand shocks in Chinese export destinations (countries that import goods from China)

[14] We derive this estimate using the 5 year effect results from Table 3 for PM, and 5 year effect results from Table 6 for infant mortality.
[15] We derive this estimate using the IV results from Table IV, which suggest mortality reductions of 5 fewer deaths per 100,000 live births per unit of TSP.

during the 2008 global financial crisis. Demand shocks from areas across the globe filter through local economies via reduced demand for goods. This can affect local $PM_{2.5}$ concentration differently across counties in China due to both (1) differences in the exposure of local economy to export, and (2) variation in the demand shocks themselves.

Severe air pollution in China will likely persist into the near future as vehicle ownership continues to rise and the manufacturing sector and electricity generation rely heavily on fossil fuel. Recent national polices outlined in the 13^{th} 5-year plan call for significant reduction in $PM_{2.5}$, which will entail significant cost through technology adoption and transition to cleaner energy. Our study contributes to our understanding of the potential health benefit from pollution reduction, a key component in the cost-benefit analysis of air pollution regulations in China.

Our results suggest long-term exposure to $PM_{2.5}$ (measured as a rolling 3-year average) leads to statistically and economically significant increases in cardiorespiratory and respiratory mortality, especially among individuals 65 years old and above. Our analysis provides suggestive quasi-experimental empirical evidence of a concave dose-response function. Using a linear spline with a knot point at the median in our data, we find per-unit reductions in ambient $PM_{2.5}$ have approximately 1.5 times the benefit at lower levels of baseline $PM_{2.5}$. This suggests one should use caution when using the benefit transfer approach to infer the benefit of environmental regulation in developing countries based on evidence from developed countries, and provides a framework for considering how early pollution reductions can lay the groundwork for greater gains in the future.

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Table 1: Summary statistics

Variables	Mean	Min	Max	N
PM2.5 Concentration, *μg/ m³*	44.14	1	117	5652
	(24.02)			
PM2.5 Concentration (population weighted), *μg/ m³*	45.73	1	117	5652
	(23.97)			
All-cause mortality, *per 100,000 persons*	104.85	0	808	5583
	(150.76)			
Respiratory Mortality, *per 100,000 persons*	15.39	0	323	5583
	(34.19)			
Cardiovascular Mortality, *per 100,000 persons*	42.51	1	420	5602
	(75.50)			
Top 5 Destination Countries' Import, *US$ billion*	72.21	0	197	5592
	(41.95)			
City-level export in 2000, *billion yuan*	6.83	0	132	5736
	(19.14)			
GDP per Capita, *yuan/person*	22453.34	841	142262	5688
	(23286.56)			
Population Density, *persons/ km²*	666.28	2	2930	5700
	(775.33)			
Local Government Spending,*100 million yuan*	74.34	0	2525	5700
	(266.86)			
Hospital Beds per 10,000 persons	6860.59	0	93000	5664
	(14488.68)			
No of Employees, *10,000 persons*	29.43	0	564	5700
	(76.77)			
Precipitation, *mm*	326.79	69	673	5772
	(86.40)			
Humidity,*1%*	66.79	34	83	5772
	(10.17)			
Wind Speed, *mph*	2.13	1	5	5772
	(0.71)			
Temperature, *℉*	56.94	9.14	[36,77]	5772

Note: Standard deviations are in parenthesis.

Table 2: The impact of PM2.5 on all-cause mortality

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5	0.001	0.002	0.003	0.020**	0.026**	0.022***
	(0.001)	(0.001)	(0.002)	(0.010)	(0.011)	(0.008)
ln(GDP per capita)	-0.003	0.038	0.088			0.059
	(0.049)	(0.053)	(0.075)			(0.086)
ln(population density)	-0.062	-0.074*	-0.025			-0.027
	(0.040)	(0.043)	(0.052)			(0.052)
ln(government spending)	-0.124***	-0.093*	-0.072			-0.128
	(0.035)	(0.053)	(0.085)			(0.099)
ln(hospital beds)	-0.015	-0.036	0.039			0.005
	(0.026)	(0.029)	(0.070)			(0.096)
ln(employment)	0.085**	0.065*	0.026			0.042
	(0.034)	(0.036)	(0.036)			(0.039)
Precipitation	1.5E-04	1.4E-04	-2.0E-04		5.4E-05	-9.2E-05
	(3.3E-04)	(3.3E-04)	(4.5E-04)		(0.001)	(4.83E-04)
Humidity	9.4E-05	-0.001	-0.004		-0.001	-0.002
	(0.006)	(0.006)	(0.010)		(0.010)	(0.010)
Wind speed	0.004	-0.002	0.038		0.005	0.019
	(0.061)	(0.061)	(0.065)		(0.066)	(0.065)
Temperature <40F	-0.002	-0.001	0.005		0.011*	0.010*
	(0.002)	(0.002)	(0.004)		(0.006)	(0.005)
Temperature (40-60 F)	0.000	-0.000	0.002		0.005	0.004
	(0.001)	(0.001)	(0.003)		(0.003)	(0.003)
Temperature (80-90 F)	-0.004*	-0.003	-0.005		-0.008**	-0.009**
	(0.002)	(0.002)	(0.004)		(0.004)	(0.004)
Temperature (⩾90F)	0.001	0.003	0.001		0.009	0.007
	(0.006)	(0.007)	(0.011)		(0.011)	(0.011)
Constant	4.433***	4.283***				
	(0.811)	(0.795)				
County-age-gender FE	NO	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES	YES
Observations	5367	5367	5188	5188	5188	5188
First-stage F-statistics	-	-	-	18.63	17.98	30.75
(p-values)				(0.000)	(0.000)	(0.000)

Note: [1] the dependent variables are in logarithm; PM2.5 are past 3-year mean PM2.5 concentration serving as a proxy for long-term exposure to PM2.5; the reference group for temperature bins is 60-80 F; [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively; [3] standard errors clustered at the county level are in parenthesis.

Table 3: The effect of PM2.5 on mortality by age

	All ages	**Below 20**	**[20, 65)**	**65&above**
Panel A: all-cause mortality				
PM2.5	0.022***	0.016	0.024***	0.026**
	(0.008)	(0.011)	(0.009)	(0.011)
All other controls	YES	YES	YES	YES
Panel B: Cardiorespiratory mortality				
PM2.5	0.021**	0.021**	0.022**	0.027**
	(0.009)	(0.010)	(0.010)	(0.012)
All other controls	YES	YES	YES	YES
Panel C: Respiratory mortality				
PM2.5	0.021***	0.025**	0.021***	0.032*
	(0.007)	(0.010)	(0.008)	(0.017)
All other controls	YES	YES	YES	YES
Observations	5188	1709	2605	874
First-stage F-statistics	30.75	32.65	30.72	19.92
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)

Note: [1] the dependent variables are in logarithm; [2] all regressions include socio-economic and weather controls, year FE, county-age-gender FE; [3] *, ** and *** are significance levels at 1%, 5% and 10%, respectively; [4] standard errors clustered at the county levels are in parenthesis.

Table 4: Robustness check: linear-linear regressions by age

	All ages	Below 20	[20, 65)	65&above
Panel A: All-cause mortality				
PM2.5	1.685^{***}	0.299	1.434^{***}	11.113^{***}
	(0.576)	(0.237)	(0.490)	(4.137)
All other controls	YES	YES	YES	YES
Panel B: Cardiorespiratory mortality				
PM2.5	0.754^{**}	0.027	0.387^{**}	8.023^{**}
	(0.322)	(0.081)	(0.185)	(3.217)
All other controls	YES	YES	YES	YES
Panel C: Respiratory mortality				
PM2.5	0.330^{***}	0.043	0.225^{***}	3.461^{**}
	(0.110)	(0.072)	(0.060)	(1.407)
All other controls	YES	YES	YES	YES
Observations	5188	1709	2605	874
First-stage F-statistics	30.75	32.65	30.72	19.92
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)

Note: [1] the dependent variables are in levels; [2] all regressions include socio-economic and weather controls, year FE, county-age-gender FE; [3] *, ** and *** are significance levels at 1%, 5% and 10%, respectively; [4] standard errors clustered at the county level are in parenthesis.

Table 5: Spline regressions

	All-cause mortality	Cardiorespiratory mortality	Respiratory mortality
PM2.5 below 42 µg/m3	1.410**	0.572*	0.255**
	(0.655)	(0.340)	(0.128)
PM2.5 above 42 µg/m3	0.922***	0.442**	0.147***
	(0.291)	(0.176)	(0.057)
All other controls	YES	YES	YES
First-sate Angrist-Pischke F-statistics (p-values)			
PM2.5 below 42 µg/m3	7.85	7.85	7.85
	(0.0000)	(0.0000)	(0.0000)
PM2.5 above 42 µg/m3	21.68	21.68	21.68
	(0.0000)	(0.0000)	(0.0000)
Stock-Yogo critical values (10%)	*10.22*	*10.22*	*10.22*
Observations	5188	5188	5188

Note: [1] the dependent variables are in levels; [2] all regressions include socio-economic and weather controls, year FE, county-age FE; [3] *, ** and *** are significance levels at 1%, 5% and 10%, respectively; [4] standard errors clustered at the county level are in parenthesis.

Figure 1: PM2.5 Concentration in 2010 (3-year Average)

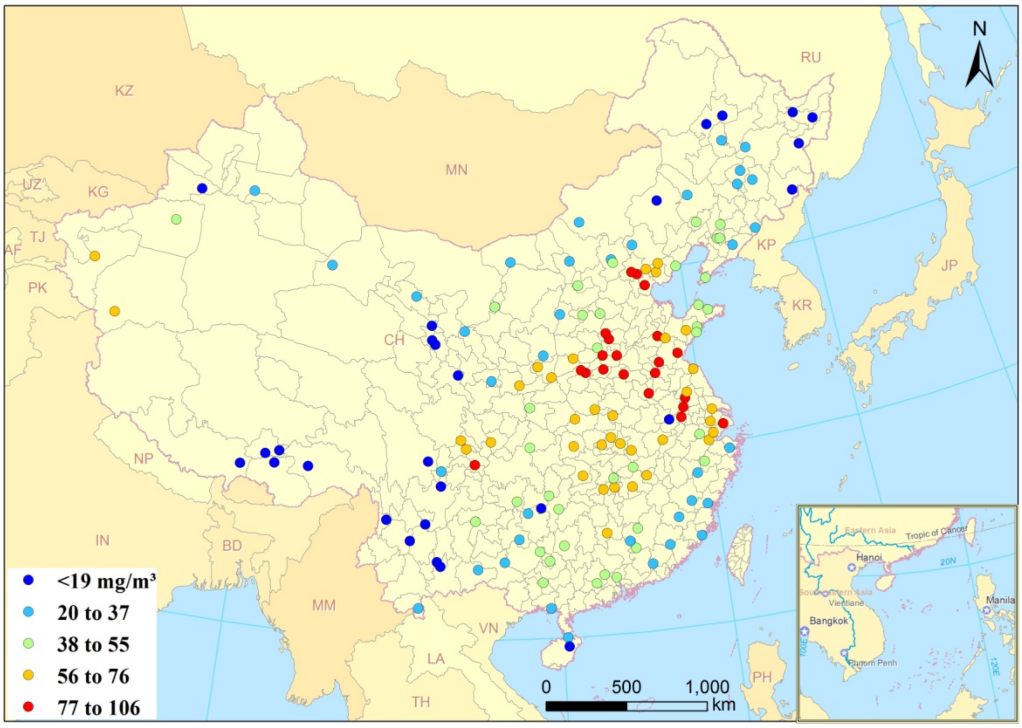


Figure 2: Changes in 3-year Average PM2.5 Concentration, 2004-2010

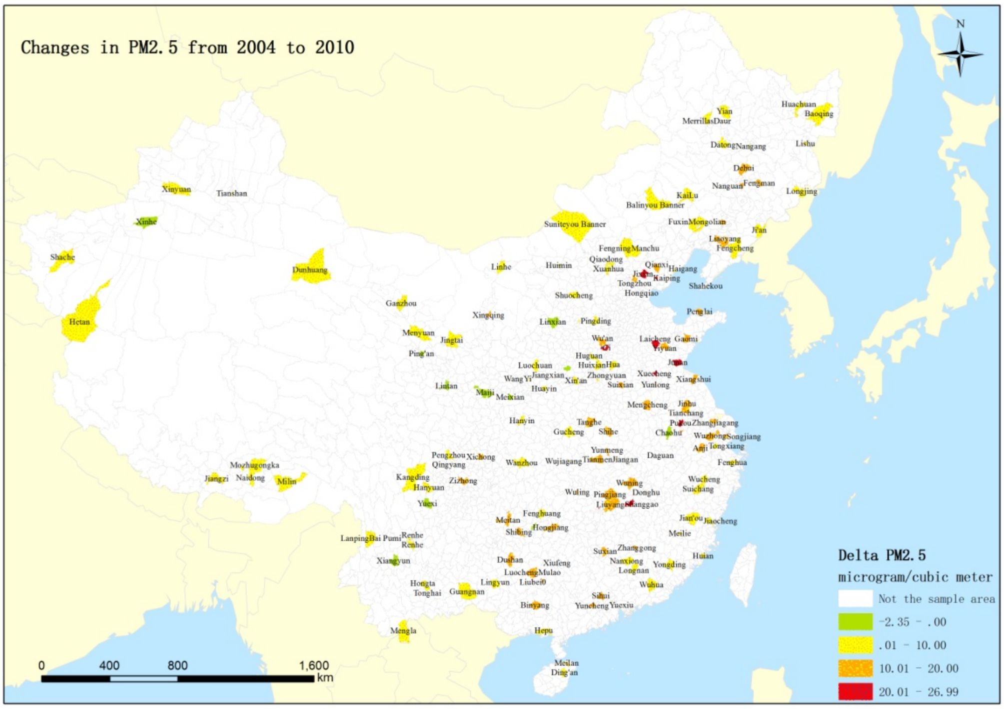


Figure 3: Trends in Mortality, Past 3-year Average PM2.5 Concentration, Top 5 Imports and GDP (2004-2010)

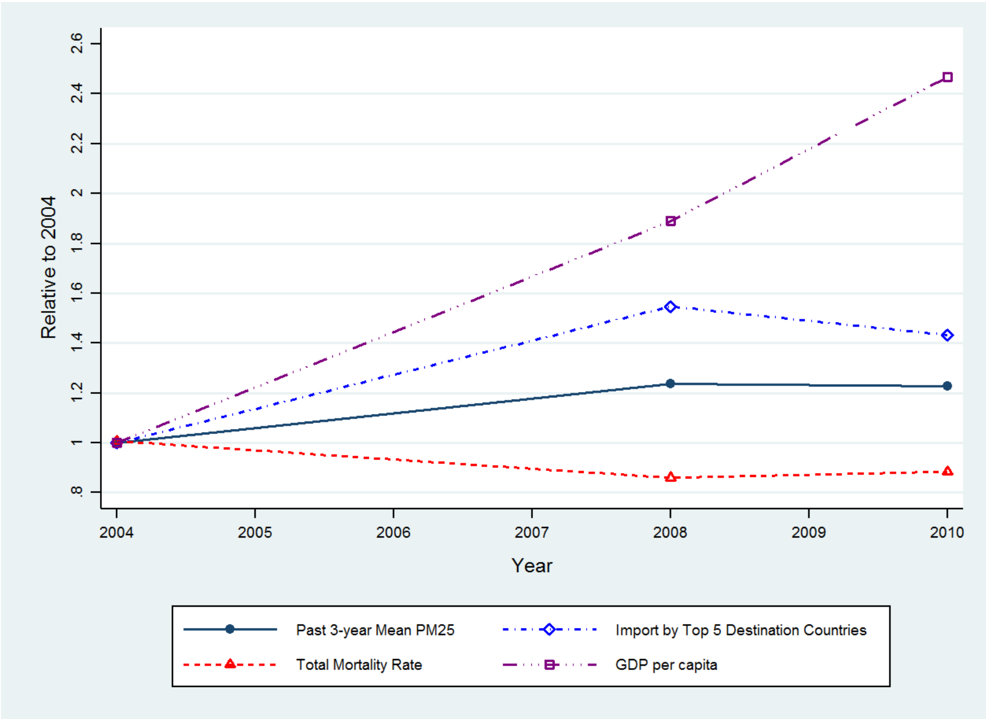


Figure 4:Mortality, by change in PM2.5 (2004-2010)

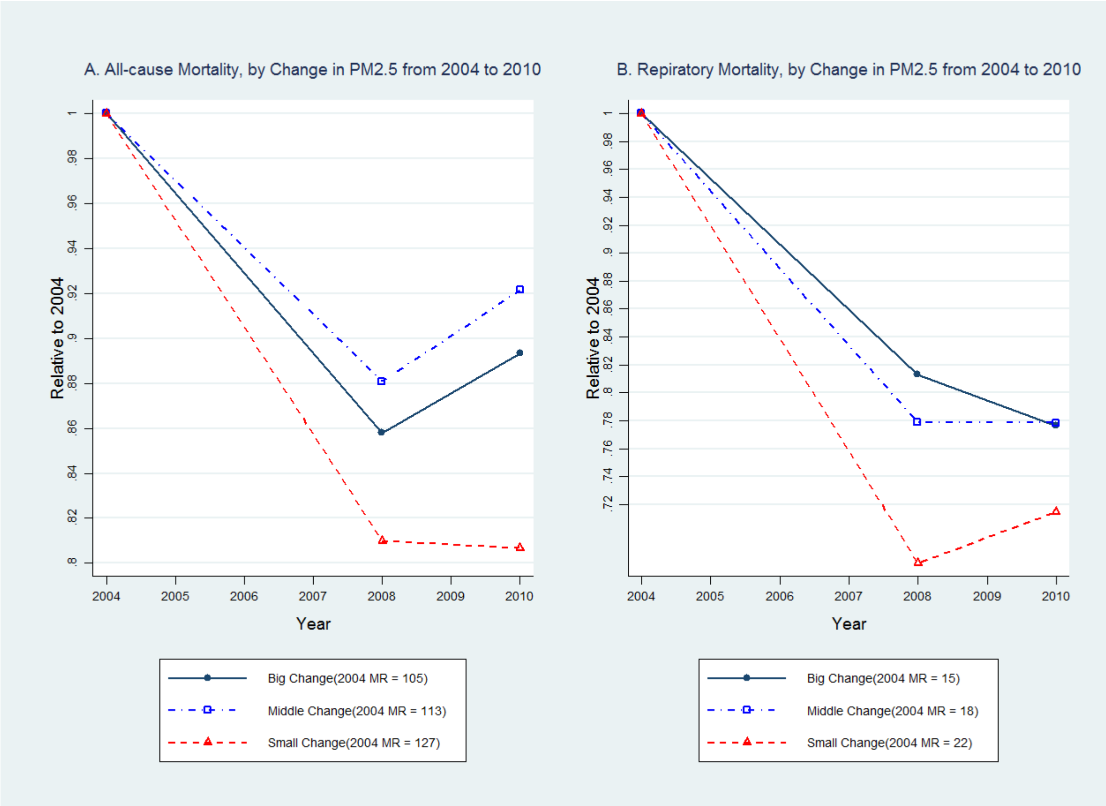


Figure 5:PM2.5 concentration, by change in PM2.5 (2004-2010)

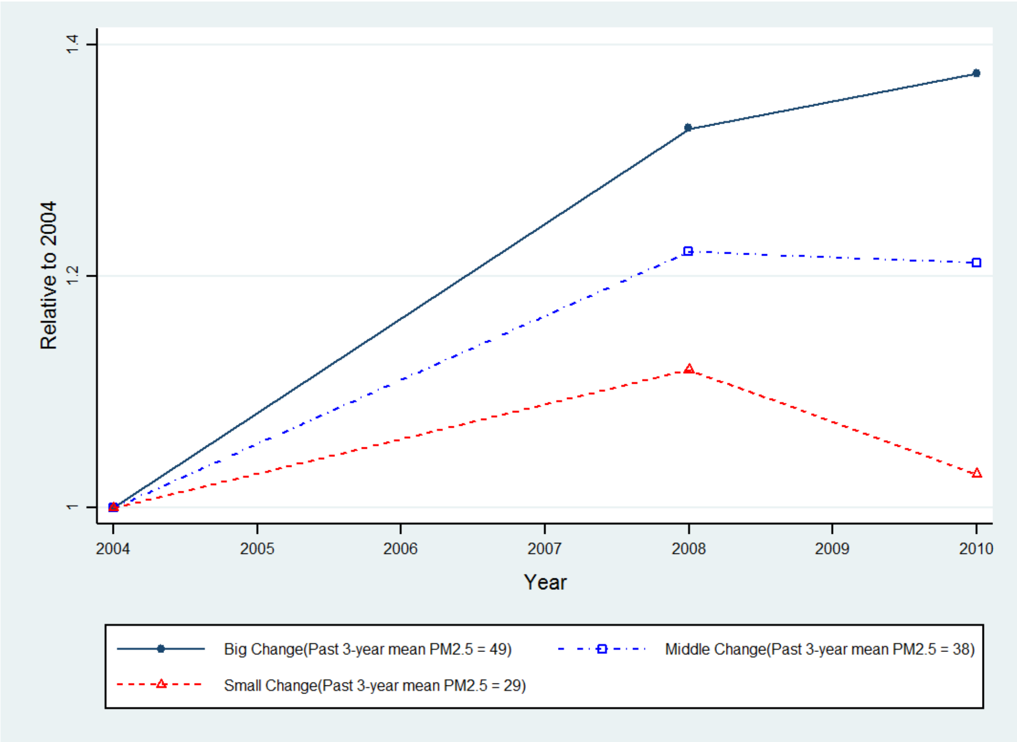
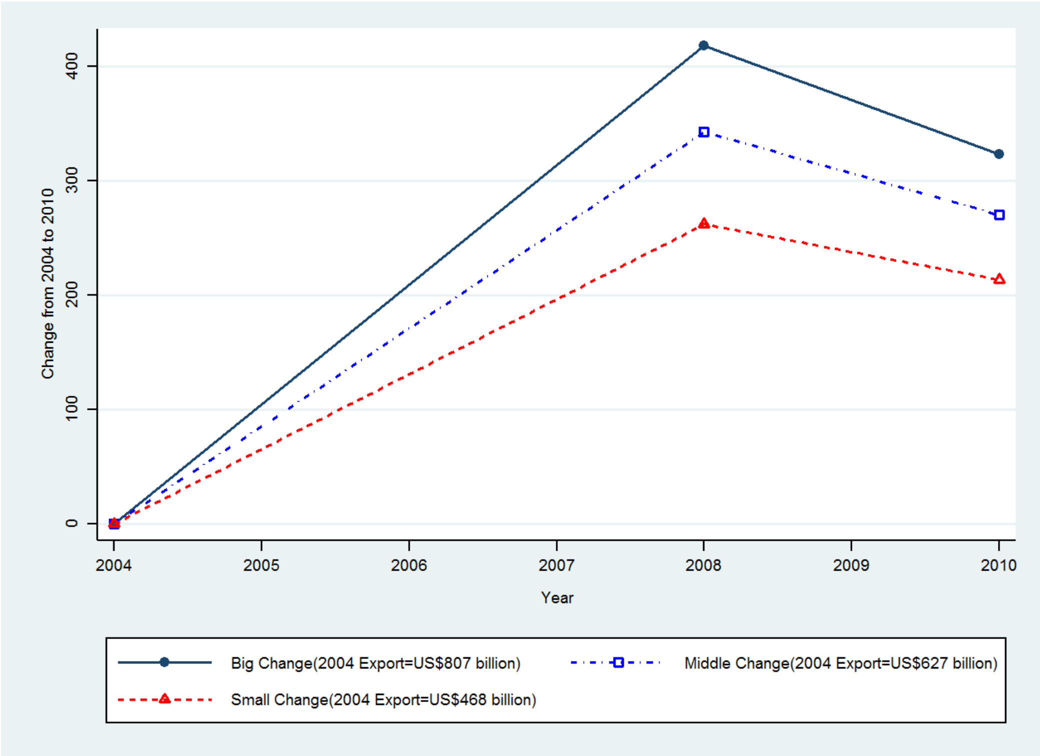


Figure 6: Import by Top 5 Destination Countries, by Change in PM2.5 (2004-2010)



Appendix Table 1: Effect of PM2.5 on mortality (1st stage)

	(1)	(2)	(3)
ln(export in 2000)*Top-5 Import	0.001***	0.001***	0.001***
	(1.3E-04)	(1.3E-04)	(1.2E-04)
Precipitation		-0.007	-0.004
		(0.008)	(0.008)
Humidity		-0.192	-0.166
		(0.183)	(0.175)
Wind speed		1.216	1.109
		(1.581)	(1.488)
Temperature below 40F		-0.263*	-0.197
		(0.152)	(0.145)
Temperature (40-60 F)		-0.143	-0.088
		(0.101)	(0.094)
Temperature (80-90 F)		0.073	0.101
		(0.091)	(0.094)
Temperature (90 F and above)		-0.184	-0.248
		(0.211)	(0.219)
ln(GDP per capita)			1.880
			(2.016)
ln(population density)			-1.304
			(1.322)
ln(government spending)			4.306*
			(2.447)
ln(hospital beds)			1.848
			(2.864)
ln(employment)			-2.656*
			(1.572)
County-gender-age FE	YES	YES	YES
Year FE	YES	YES	YES
No of observations	5188	5188	5188
First-stage F-statistics	18.63	17.98	30.75
(p-values)	(0.0000)	(0.0000)	

Appendix Table 2: Effect of PM2.5 on mortality (by gender, 1st stage)

	Male	Female
ln(city export in 2000)* Top 5 import	0.001***	0.001***
	(1.2E-04)	(1.2E-04)
ln(GDP per capita)	1.870	1.890
	(2.012)	(2.020)
ln(population density)	-1.269	-1.341
	(1.312)	(1.332)
ln(government spending)	4.324*	4.288*
	(2.435)	(2.461)
ln(hospital beds)	1.926	1.766
	(2.854)	(2.876)
Employment	-2.617*	-2.695*
	(1.562)	(1.582)
Precipitation	-0.004	-0.004
	(0.008)	(0.008)
Humidity	-0.170	-0.162
	(0.174)	(0.175)
Wind speed	1.069	1.151
	(1.489)	(1.487)
Temperature below 40F	-0.191	-0.202
	(0.144)	(0.145)
Temperature (40-60 F)	-0.084	-0.091
	(0.094)	(0.094)
Temperature (80-90 F)	0.101	0.102
	(0.094)	(0.094)
Temperature (90 F and above)	-0.253	-0.243
	(0.221)	(0.217)
County-gender-age FE	YES	YES
Year FE	YES	YES
No of observations	2614	2574
First-stage F-statistics	30.33	31.01
(p-values)	(0.0000)	(0.0000)

Appendix Table 3: The effect of PM2.5 on mortality by age groups (1st stage)

	All	Below 20	[20, 65)	65&above
ln(export in 2000)*Top-5 Import	0.001***	0.001***	0.001***	0.001***
	(1.2E-04)	(1.2E-04)	(1.2E-04)	(1.3E-04)
ln(GDP per capita)	1.880	2.148	1.760	1.806
	(2.016)	(2.011)	(2.014)	(2.137)
ln(population density)	-1.304	-1.338	-1.349	-0.760
	(1.322)	(1.342)	(1.316)	(1.491)
ln(government spending)	4.306*	4.748**	4.091*	4.222
	(2.447)	(2.390)	(2.472)	(2.605)
ln(hospital beds)	1.848	2.062	1.900	0.949
	(2.864)	(2.871)	(2.859)	(3.037)
ln(employment)	-2.656*	-3.404*	-2.424	-1.974
	(1.572)	(1.814)	(1.495)	(1.465)
Precipitation	-0.004	-0.002	-0.004	-0.006
	(0.008)	(0.009)	(0.008)	(0.008)
Humidity	-0.166	-0.166	-0.168	-0.149
	(0.175)	(0.184)	(0.171)	(0.172)
Wind speed	1.109	0.874	1.159	1.417
	(1.488)	(1.508)	(1.480)	(1.560)
Temperature below 40F	-0.197	-0.190	-0.195	-0.216
	(0.145)	(0.141)	(0.145)	(0.160)
Temperature (40-60 F)	-0.088	-0.116	-0.079	-0.054
	(0.094)	(0.095)	(0.094)	(0.099)
Temperature (80-90 F)	0.101	0.094	0.101	0.123
	(0.094)	(0.092)	(0.095)	(0.099)
Temperature (90 F and above)	-0.248	-0.186	-0.260	-0.316
	(0.219)	(0.230)	(0.215)	(0.234)
County-age-gender FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
No of observations	5188	1709	2605	874
First-stage F-statistics	30.75	32.65	30.72	19.92
(p-values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Appendix Table 4: Long-term effect of pollution on mortality

Sources	Dose, additional	Response
Ebenstein et al. (2017)	a 10-µg/ m^3 increase in annual mean PM_{10} concentration	8%-11% increase in cardiorespiratory mortality in Northern China (RD) 2% increase in cardiorespiratory mortality in Northern China (OLS)
Zhou et al. (2015)	a 10-µg/m^3 increase in monthly mean PM_{10} concentration	Associated increase in adult respiratory mortality by 1.05% (OLS)
Pope et al. (2009)	A 10-µg/m^3 increase in annual mean $PM_{2.5}$ concentration	0.61±0.20 years of associated decrease in life expectancy in the USA (OLS)
Yin et al. (2017)	A 10-µg/m^3 increase in daily $PM_{2.5}$ concentration	a 0.44% increase in daily number of deaths in China (OLS)
Janke et al. (2009)	a 10-µg/m^3 increase in annual mean PM_{10} concentration	Associated increase in all-cause mortality by 2.8% in England (OLS)
Shi et al. (2016)	a 10-µg/m^3 increase in annual exposure to $PM_{2.5}$	Associated increase in all-cause mortality by 7.52% for the elderly (age>65) in USA (OLS)
Our estimates		
OLS	10-µg/m^3 increase in 3-year average $PM_{2.5}$ concentration	1-3% increase in all-cause mortality
IV	10-µg/m^3 increase in 3-year average $PM_{2.5}$ concentration	22% increase in all-cause mortality and 21% increase in cardiorespiratory mortality 21% increase in respiratory mortality