Journal of Environmental Economics and Management 117 (2023) 102759

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The mortality impact of fine particulate matter in China: Evidence from trade shocks[☆]

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ARTICLE INFO

JEL classification:
Q53
Q56

Keywords:
$PM_{2.5}$
Mortality
Dose-response function
Nonlinearity

ABSTRACT

We use county-level panel data to estimate the long-run effect of fine particulate matter ($PM_{2.5}$) pollution on mortality in China. Our causal inference relies on changes in local pollution via wind transport and demand shocks of Chinese products from export destinations amid the global economic crisis during the late 2000s. We find an economically and statistically significant impact of long-term exposure to $PM_{2.5}$ on cardiovascular and respiratory mortality, and the effect is the largest for those 65 years and older. Using the substantial variation in pollution levels both across time and space in China, we provide evidence of a concave dose-response function, with diminishing marginal mortality impacts of pollution at levels beyond those in developed nations.

1. Introduction

Exposure to particulate matter smaller than 2.5 μm ($PM_{2.5}$) varies substantially across nations. During the 2011–2015 period, less than 20% of the population in OECD and high-income countries were exposed to annual mean concentrations above the WHO guideline of 10 μg per cubic meter of air (μg/m^3), while more than 90% of the population in low-and-middle income countries faced pollution above the WHO guidelines. Studies show that air pollution generated substantial health costs in developing nations: half of premature deaths in the world attributed to air pollution are from China and India alone (Lancet Commission, 2016).

Studies of the causal impact of air pollution on health often take place using areas with comparatively low levels of air pollution (e.g., OECD countries).[1] This paper aims to better understand the health and pollution relationship in more polluted environments. We examine the causal impact of long-term exposure to $PM_{2.5}$ on mortality in China, where the annual concentration of $PM_{2.5}$ was

☆ Yazhen Gong acknowledges the financial support of the National Natural Science Foundation of China (grant No. 71773135). Authors declare no conflict of interest and have no other relevant or material financial interests that relate to the research described in this paper.

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[1] A partial list of this literature includes Barreca et al., 2016; Chay and Greenstone (2003); Chay and Greenstone, 2003; Chen et al. (2013), Chen et al., 2017; Ebenstein et al., 2017; He et al. (2016); Janke et al. (2009); Janke et al., 2009; Knittel et al., 2015; Schlenker and Walker (2015); Deschênes,2017.

https://doi.org/10.1016/j.jeem.2022.102759
Received 11 August 2020; Received in revised form 3 October 2022; Accepted 8 November 2022
Available online 19 November 2022
0095-0696/

consistently over 50 μg/m^3.[2] We use a panel data set of the 161 county and city-districts covered by the Disease Surveillance Point System (DSPS) of Chinese Center for Disease Control and Prevention (CDC) for the years of 2004, 2008, and 2010. We combine this with satellite measures of estimated long-term average $PM_{2.5}$ exposure levels.

In estimating the long-term mortality impact of air pollution, we need to deal with the key identification challenge that economic growth drives both higher pollution levels and health care improvements, especially in rapidly developing nations. To address this potential endogeneity, we construct an instrumental variable (IV) for $PM_{2.5}$ in which we leverage the severe global economic recession in the late 2000s. The global decrease in demand for China-produced manufactured goods generated shocks to demand for Chinese exports. We propagate these global shocks to the local level using variation in export destinations and wind patterns across Chinese prefectures (i.e., cities). Our identifying assumption is that the global economic recession affected prefectures in China differently due to cross-regional differences in exposure to trade, both in terms of total share of economic production and dependence on different export destinations which were affected differentially by the global economic crisis. To further address concerns of bias from local economic effects, we instrument for pollution levels in a given county using shocks from *adjacent* areas, employing information on prevailing wind direction in the region. Our IV thus uses local variation in three factors for a given county: (1) the (pre-determined) size of the export sector of nearby prefectures, (2) primary destinations for exports from nearby prefectures, and (3) prevailing wind direction bringing pollution from nearby prefectures.

An additional empirical challenge lies in the lack of reliable pollution measurements in developing nations. This means an increased likelihood of measurement error in region-specific pollution exposure, or biases driven by misreporting (Ghanem and Zhang, 2014; Greenstone et al., 2019). During the period of our mortality data, there were no reliable ground-level $PM_{2.5}$ monitoring data in China, which became available starting in 2013 at the national level (Barwick et al., 2019). Instead, we use three-year average $PM_{2.5}$ levels derived from satellite data on measurements of Aerosol Optical Depth (AOD). Due to its advantage in rich spatial coverage, satellite-based pollution data have been used in many recent studies (e.g., van Donkelaar et al., 2015; Zou, 2021; Greenstone et al., 2021).

By leveraging air pollution variation induced by the trade shocks due to notably the global financial crisis of 2007–2008, we find long-term, regular exposure to $PM_{2.5}$, as measured by three-year averaged pollution levels, increases all-cause and cardiorespiratory mortality in an economically and statistically significant manner. The largest impacts are for those 65 years and older, which foretells of a rising future disease burden given a growing older population in China. Using $PM_{2.5}$ variation in both location and time within China, we examine the pollution dose-response function across higher and lower levels of ambient pollution. We find larger marginal mortality impacts at lower concentrations, indicating a concave dose-response function. This aligns with recent findings that air quality improvements may result in only "modest reductions in burden in the most polluted countries unless $PM_{2.5}$ concentrations decline markedly" (Cohen et al., 2017). It also highlights the potential complications of extrapolating marginal effects of pollution to more heavily polluted areas using studies in low-pollution nations.

Our results align with the growing body of literature showing that higher levels of ambient air pollution increase mortality.[3] China's higher pollution levels make our estimates most closely comparable to Chen et al. (2013), He et al. (2016) and Ebenstein et al. (2017), all of which study pollution and mortality in China. We both build on and add to these earlier findings in three ways. First, Chen et al. (2013) estimate the impact of total suspended particulates (TSP), and He et al. (2016) and Ebenstein et al. (2017) examine particulate matter smaller than ten microns (PM_{10}). We estimate the impact of $PM_{2.5}$ on mortality, as health literature suggests finer particles such as $PM_{2.5}$ carry larger adverse health impacts because they may be more toxic, can penetrate deeper into lungs, and remain suspended for longer period of time than larger particles (Pope and Dockery, 2006).

Second, we offer an alternative identification strategy. Both Chen et al. (2013) and Ebenstein et al. (2017) focus on pollution's long-term impact by using a regression discontinuity (RD) approach based on the Huai River heating policy in China, which relies on purely cross-sectional variation in air pollution due to differences in central heating policy across the Huai River. Our approach uses both spatial and temporal variation. He et al. (2016) estimate the short-term impact based on the shock to air pollution due to the singular event of the Olympic games in Beijing in 2008, which is informative but cannot speak to longer-run exposure.

Third, we examine the shape of the dose-response function by considering effects above and below the median $PM_{2.5}$ levels in China (42 μg/m^3) during our study period. Different parts of China experienced wide variation in average ambient pollution levels (rather than one-time extreme shocks), which is a key factor that allows us to jointly estimate marginal effects at both lower and higher levels of pollution using a knotted spline.

Section 2 of this paper provides background on China's air pollution challenge, describes our various data sources, and explains the design of our IV strategy. Section 3 discusses our empirical framework. Section 4 presents empirical results, and Section 5 concludes.

[2] China's $PM_{2.5}$ concentration was more than six times of that in the United States (8 μg/m^3) in 2014 (WHO, 2016), almost three times of that (21 μg/m^3) during the period of 1979–1983 (Pope et al., 2009) and almost twice of that (30 μg/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 59 μg/m^3) substantially exceed levels in India (28 μg/m^3) (Apte. et al., 2015). The annual standard set by China's Ministry of Environmental Protection (MEP) is 35 μg/m^3.

[3] While earlier work focused on infants (Chay and Greenstone, 2003; Chen et al., 2005; Chen et al., 2017; Knittel et al., 2015), recent research shows negative effects for adults as well (Anderson, 2019; Barreca et al., 2021; Deryugina et al., 2019).

2. Background and data

2.1. Background

Understanding the health impacts of air pollution in modern China is important for informing evidence-based policymaking as the government tries to balance two recent major policy shifts. As incomes rise and residents become more informed on the potential health impacts of air pollution, demand for environmental quality has generated pressure for policy change. Improving air quality has become a major policy goal of the Chinese central government (Greenstone et al., 2021). China's 11th Five Year Plan (FYP), spanning 2006–2010, first proposed monitoring $PM_{2.5}$ in major cities in China.[4] The 13th FYP (2016–2020) explicitly regulates $PM_{2.5}$ pollution as a key policy goal, a dramatic shift in China's long-standing strategy of prioritizing economic growth over environmental concerns. Since the 11th FYP, the central government has undertaken unprecedented regulatory changes on multiple fronts to combat environmental challenges (Karplus et al., 2021).

In another major move, recent national plans such as the One-Belt One-Road initiative aim to reduce economic disparity across different regions, encouraging manufacturing activities to move from the east coast to the west and improving public infrastructure and investment in the western region. These economic development strategies could lead to significant changes in environmental quality in areas where environmental awareness may be weaker and access to healthcare is still poor. This 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 sources and descriptive statistics

We assemble several data sets on mortality, air pollution, trade, and socioeconomic conditions at various administrative levels from multiple sources covering the years 2004, 2008, and 2010. The smallest administrative units in our data are counties and city-districts. In the Chinese system, provinces and then prefecture-level cities (henceforth prefectures) are the first two levels of administrative unit, and prefectures contain multiple counties or city-districts.[5] Our data are either at the prefecture level or at the county level.

2.2.1. Mortality data

Mortality data are from the Disease Surveillance Point System (DSPS) of the Chinese Center for Disease Control and Prevention (CDC) established by Chinese government. The DSPS covers 161 geographic counties/city-districts across China. To represent national population and mortality, the government uses a multi-stage cluster population probability sampling method (Yassin et al., 2012; Zhou et al., 2015). Since the early 2000s, the DSPS covers more than 81.5 million people, approximately 6% of the Chinese population.[6] We obtained restricted-use mortality statistics by age group, gender, and cause of death for all 161 counties covered by DSPS for 2004, 2008 and 2010 (similar mortality statistics were not available to us for other years). Fig. 1 shows the locations of the 161 counties/city-districts in our data (hereafter we refer to both geographies as counties for simplicity).

Several recent studies use the DSPS data including Chen et al. (2013), He et al. (2016), Ebenstein et al. (2017), and Barwick et al. (2019). 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 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).

2.2.2. Pollution data

Our focus is on the mortality effects of extended pollution exposure rather than temporary pollution shocks, making it closer in concept to Chen et al. (2013) and Ebenstein et al. (2017). Epidemiology literature often refers to "long-term" ambient pollution exposure as lengths of a year or more (e.g., Pope et al., 2002; Brunekreef and Holgate, 2002; Hoek et al., 2013; Miller et al., 2007), and estimating pollution health effects over such longer periods requires a reliable and regular measure of ambient air quality. Prior to 2013, there was no systematic monitoring of $PM_{2.5}$ by the Chinese government (Barwick et al., 2019), and other pollution measures (such as the Air Pollution Index) are subject to widespread manipulation (Ghanem and Zhang, 2014; Greenstone et al., 2019). Instead, we rely on $PM_{2.5}$ concentrations derived from satellite AOD observations.[7]

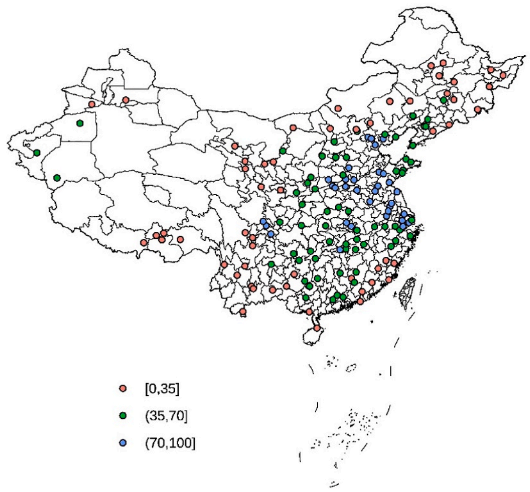
[4] FYPs are passed by the Standing Committee of National People's Congress, the highest-level of government that has the power to legislate. The first FYP was made for the period of 1953–1957.

[5] There are 333 prefecture-level cities or prefectures in China.

[6] For detailed discussions on the sampling of DSPS which was designed by China's CDC to represent the national population and mortality trends, please refer to Yassin et al. (2012), Zhou (2010) and Zhou et al. (2015). Zhou (2010) evaluate the representativeness of the DSPS and conclude that the DSPS has good representativeness in both urban and rural areas.

[7] 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). We retrieve data from the Global Annual $PM_{2.5}$ Grids Database which is derived from AOD data from MODIS (Moderate Resolution Imaging Spectroradiometer), MISR (Multi-angle Imaging SpectroRadiometer), and SeaWiFS (Sea-Viewing Wide Field-of-View Sensor).

(a) Average $PM_{2.5}$ (in /m3) during 2008-2010



(b) Changes in Three-year Average PM2.5 from 2004 to 2010

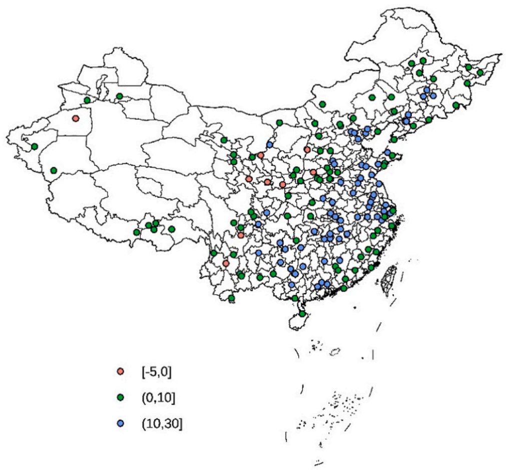


Fig. 1. $PM_{2.5}$ Concentration in Sample Areas (a) Average $PM_{2.5}$ (in μg/m^3) during 2008–2010
Note: [1] The base map of China was obtained from the Ministry of Natural Resources of the People's Republic of China website (http://bzdt.ch.mnr.gov.cn/browse.html?picId=%224o28b0625501ad13015501ad2bfc0480%22 accessed on 20 June 2022), Drawing review NO GS(2020)4619. No modification has been made for the base map. [2] Panel (a) shows the three-year average $PM_{2.5}$ (in μg/m^3) during 2008–2010 in the sample areas (counties or city districts). Panel (b) shows the change of three-year average $PM_{2.5}$ from 2004 (2002–2004) to 2010 (2008–2010). All $PM_{2.5}$ data are from Aerosol Optical Depth readings – see Section 2 for details.

Several studies on the health impact of air pollution have used these data (e.g., Barreca et al., 2021; van Donkelaar et al., 2015), which contain a series of three-year running averages of fine particulate matter, spanning the 1998–2012 period, across geographic grids with a resolution of $0.1 \times 0.1°$. We transform grid-level data to measures for the 161 counties in our mortality data using longitude and latitude information for each county. To match to observed deaths in 2004, 2008, and 2010, we use the three-year average corresponding to each mortality year plus the prior 2 years as the measure of long-term exposure to $PM_{2.5}$. We hereafter refer to this value as our measure of $PM_{2.5}$ concentration.[8]

2.2.3. Trade data

We leverage both China-wide and prefecture-level trade data from 2000 to 2010 as a driver of plausibly exogenous variations in

[8] For example, the pollution level reported for 2004 is an average of pollution levels in 2002, 2003, and 2004.

local air pollution. Our IV interacts two trade variables covering the international demand for Chinese exports: the total value of exports from the whole China to various destinations, and the role those destinations play in local, prefecture-specific export totals. The annual export demand from China captures differential demand shocks from export destinations such as the United States and India. The local shares propagate these China-wide shocks to the local level using differences in regional trade intensity and primary export destinations. We collect information on total Chinese exports to countries/regions in each year during 2001–2010 from the World Bank's World Development Indicators, and information on local trade intensity from China's Customs database. We describe our IV construction using these data in detail below.

2.2.4. Socioeconomic data

Socioeconomic conditions at the local level can affect both pollution and health outcomes. In the Chinese context, prefectures are hubs of local economic development as well as healthcare services. Residents in counties (or rural areas) usually go to prefecture hospitals 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 prefecture level.

Given the above context, we collect prefecture-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 three-year average for each variable for 2004, 2008, and 2010 to be consistent with the timing of our $PM_{2.5}$ exposure variable.

2.2.5. Weather data

We collect weather information from the National Bureau of Meteorology on temperature, precipitation, humidity, solar radiation, and wind speed for each station, and aggregate daily information to the annual level. 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 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 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 three-year average values to be consistent with the timeframe of the pollution variable.

In addition to varying weather data, we use regular prevailing wind direction as part of our IV construction. Note we do not use *shocks* to wind direction, but average persistent differences in *prevailing* wind direction. We base our use of average prevailing wind direction rather than daily shocks on several considerations. First, mortality data are annual, so we cannot match daily shocks to daily mortality variation. Second, our objective is to identify the long-term (the past three-year average) rather than short-term (daily) effects of $PM_{2.5}$ pollution on mortality. In this sense, the wind direction on a single day, or even variation in seasons across the year, is not as relevant as the general contribution of wind direction to average ambient pollution an individual experience. Short-term variation should wash out in our case – seasonal differences persist across time, and the net of such differences is what matters for long-term exposure variation.

To build our measure of wind direction, we begin with daily information on wind directions and the centroids of all prefectures. Assuming no abrupt change in average prevailing wind direction one year to another within one decade, we identify all prefectures that are, on average, upwind of a given prefecture. We do so by averaging daily wind direction during 2011 to a single direction as the prevailing wind direction for our study period (2001–2010). Essentially, we use cross-sectional, rather than temporal, variations in wind direction in our categorization of upwind prefectures.

Use of prevailing wind direction presents a challenge for endogeneity of health effects. If, for example, individuals sort based on prevailing winds, wind direction violates the exclusion restriction. While shocks to wind direction may help with sorting concerns, one cannot use them to identify chronic exposure, only acute effects (Deryugina et al., 2019). The economics literature shows various roles of wind and pollution in location, and it remains an open question as to how much of a concern sorting behavior should be. Anderson (2019) shows property values are similar on both the upwind and downwind sides of a major freeway, despite very different levels of traffic pollution exposure, suggesting sorting is not an issue. Using atmospheric pollution models, Barreca et al. (2021) show that changes to wind-based particulate exposure from power plants did not shift migration patterns in the US. However, Heblich et al. (2021) argue that historical wind patterns moving industrial pollution eastward can explain up to 20% of observed neighborhood segregation in modern cities in England. One possible explanation for differential results is how well one might observe pollution differences. Anderson (2019) deals with pollutants that are less easily observed by human senses, and Barreca et al. (2021) deals with dispersions patterns over hundreds of miles, while Heblich, Trew, and Zylberberg (2021) examine location choices within industrial cities, where differences are more starkly observed. Our case more closely parallels the former, but one should interpret our results with this in mind.

2.2.6. Summary statistics

Table 1 presents summary statistics for the variables in our study. Across 2004, 2008 and 2010, the average annual all-cause mortality rate was 974 deaths per 100,000 people. The average respiratory and cardiovascular mortality rates were 159 and 442 deaths per 100,000 people, respectively.

The aggregated three-year $PM_{2.5}$ concentration for the 161 counties was 44.98 $\mu g/m^3$ (first row of Table 1) and the population weighted average annual $PM_{2.5}$ concentration was 45.73 $\mu g/m^3$ (second row of Table 1), which are well above the WHO guideline for $PM_{2.5}$ average annual exposure of 10 $\mu g/m^3$, the US EPA's primary standard of 12 $\mu g/m^3$, and China's national annual standard of 35 μg/m^3. Even so, the 161 counties in our mortality data represent a lower average pollution level than China as a whole, as the mortality data under-sample counties in the nation's most polluted areas such as Hebei, Henan, Shandong and Shanxi. As reference, during the 2013–2015 period, the national level average $PM_{2.5}$ concentration, based on over 1000 ground-level monitoring stations available in this period, was 56 μg/m^3 with a population weighted average of 62 μg/m^3.

Greenstone et al. (2021) show the AOD-derived $PM_{2.5}$ levels based on the method from van Donkelaar et al. (2016) are consistently lower than $PM_{2.5}$ levels from ground-level monitoring stations during 2013–2018. This holds even for a fixed set of grid cells corresponding to the location of ground monitoring stations to make sure that the satellite and monitoring trends reflect pollution in similar geographic areas, and Fowlie et al. (2019) find similar differences in the United States. This highlights one source of potential measurement error in using satellite-based $PM_{2.5}$ estimates, and is one of the reasons we explore an IV model.

Table 1 also demonstrates the large variation in our estimated regular exposure to $PM_{2.5}$, ranging from 1 μg/m^3 to 117 μg/m^3, with a median $PM_{2.5}$ concentration of 42 μg/m^3. Panel (a) in Fig. 1 depicts cross-sectional variation in exposure to $PM_{2.5}$ pollution across counties in 2010, showing geographic variation in levels. Most counties in central and eastern China had higher $PM_{2.5}$ concentration levels, while counties in land-locked western China and remote regions in northeastern China have lower $PM_{2.5}$ concentrations. Our data also demonstrate large variation within area, across time. Panel (b) of Fig. 1 presents variation among sample counties as *changes* in $PM_{2.5}$ pollution from 2004 to 2010. Unlike the general trend in decreasing pollution in developed economies, in China most counties experienced a net increase in $PM_{2.5}$ concentration between 2004 and 2010, but with varied magnitudes of change. Some saw increases greater than 10 μg/m^3 while others saw smaller increases or even modest reductions. Counties experiencing the biggest increases are located in central and eastern China, while counties with smaller changes are from land-locked western China and the more remote part of northeastern China.

2.3. *Variations in $PM_{2.5}$, mortality, and trade*

We base our variation on the global financial crisis in 2008, which significantly affected international trade between China and 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 and services in 2008 and 2009 were −1% and −12%, respectively. Our premise is that reduced external demand for China's output contracted production of goods locally, driving changes in $PM_{2.5}$ concentrations in counties downwind of exporting sectors. For each prefecture, we focus on the export demand from the top five global destinations, which generates another source of regional variation in the effects of nationwide demand shocks.

One identification concern is that such demand shifts would also drive large changes in GDP, which could in turn impact health and mortality. Fig. 2 shows trends for average $PM_{2.5}$ concentrations, overall mortality rates, average of nation-wide exports to top five destination countries, and GDP per capita during 2004, 2008, and 2010.[9] Between 2004 and 2010, GDP per capita increased steadily. The decoupling of exports and local GDP suggests growth was not driven entirely by trade, but also by the expansion of domestic demand with the emerging Chinese middle-class. $PM_{2.5}$ concentration and the demand for Chinese imports of relevant countries increased overall across 2004–2010; both peaked in 2008, and decreased slightly by 2010. All-cause mortality reached its lowest level in 2008, ending slightly higher in 2010 but still below initial 2004 levels. Several factors contributed to these general mortality trends. In addition to changes in demographics, the reduction in mortality rate is likely partly due to improvement in health care and the increase in health care coverage through massive government and public campaigns during this period.

A general increasing trend of $PM_{2.5}$ concentration masks heterogenous changes in $PM_{2.5}$ concentration across counties due to differences in industry structures and socio-economic characteristics. To investigate how key variables change over time, we take the change in $PM_{2.5}$ concentration for each county between 2004 and 2010, calculate change quartiles, and divide counties into three groups: groups with small (lowest quartile), medium (25th-75th percentile), and big (greatest quartile) pollution changes.[10] Panel (a) in Fig. 3 shows striking differences across these groups in terms of changes in $PM_{2.5}$ concentration relative to 2004 levels. In the "Big increase" group, $PM_{2.5}$ concentration increased by 38%, while the "Small increase" group had only a 3% increase during the same period. $PM_{2.5}$ concentrations in the "Big increase" group increased in both 2008 and 2010, while the "Small" and "Medium" groups both reached peak $PM_{2.5}$ concentration in 2008.

Panel (b) in Fig. 3 depicts the average of changes in demand for Chinese exports among the top five destinations across counties in each of the three groups. There are two salient features. First, for counties in all three groups, total exports from China to their top five destinations peaked in 2008. Second, during 2008 and 2010, changes in total exports from China to the county-specific top five countries in the "Big increase" group were the largest. In terms of the size of export levels in 2000, counties in the "Big increase" group had the largest variation, while counties in the "Small increase" group had the smallest. These results are suggestive of the economic crisis having differential impacts on ambient air quality across counties, depending on the composition of their export-destination countries.

Fig. 4 plots the all-cause mortality rate (Panel (a)) and respiratory mortality (Panel (b)) across the three groups. These are

[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.

[10] The big increase group consists of counties with the biggest increase in $PM_{2.5}$ concentration (i.e. in the 75th percentile, with $PM_{2.5}$ concentration increased by 14.36 μg/m^3) while the small increase group consists of counties with the smallest increase (i.e. in the 25th percentile, with $PM_{2.5}$ concentration increased by 2.89 μg/m^3); The medium increase group is composed of all other counties, i.e. 25th −75th inter-quartiles.

Table 1
Summary statistics.

Variables	Mean	Min	Max	N
$PM_{2.5}$ Concentration, *μg/m*^{3}	44.98 (23.88)	1	117	5004
$PM_{2.5}$ Concentration (population weighted), *μg/m*^{3}	45.73 (23.97)	1	117	5004
All-cause mortality, *per 100,000 persons*	973.57 (1783.17)	0	9194	5028
Cardiorespiratory Mortality, *per 100,000 persons*	584.70 (1209.53)	0	6325	5028
Cardiovascular Mortality, *per 100,000 persons*	442.20 (897.92)	0	4897	4898
Top 5 Destination Countries' Import, *US$ trillion*	73.86 (41.31)	0	197	4992
City-level export in 2000, *billion yuan*	5.80 (13.75)	0	7.17	4992
GDP per Capita, *yuan/person*	23066.54 (23231.97)	841	142,262	4968
Population Density, *persons/km*^{2}	663.72 (774.83)	2	3930	4968
Local Government Spending,*100 million yuan*	56.75 (182.09)	0	1902	4968
Hospital Beds per 10,000 persons	6151.90 (14488.68)	0	807,000	4956
No of Employees, *10,000 persons*	26.48 (67.94)	0	564	4968
Precipitation, *mm*	326.79 (86.40)	64	673	5028
Humidity,*1%*	66.67 (7.67)	34	83	5028
Wind Speed, *mph*	2.18 (0.71)	1	5	5028
Temperature, *°F*	13.65 (5.08)	2	25	5028

Note: Standard deviations are in parenthesis. $PM_{2.5}$ is the three-year average during the current year and the past two years, from Aerosol Optical Depth readings. Mortality data are from the Disease Surveillance Point System from the Chinese Center for Disease Control and Prevention. Weather data are from the National Bureau of Meteorology. Economic data are from Statistical Yearbooks of Prefectural Cities in China. Trade data are from World Bank's World Development Indicators and the China Customs database.

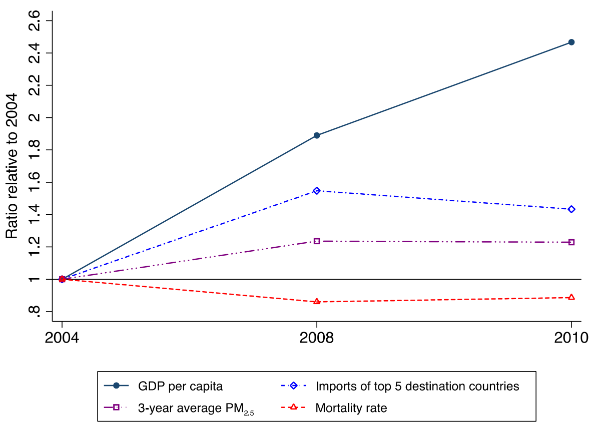


Fig. 2. Trends in GDP, Demand for Chinese Goods, $PM_{2.5}$, and Mortality during 2004–2010
Note: Figure shows the ratio of the listed four variables relative to 2004 levels at the nationwide level. To capture the demand shocks through trade, we find the top-5 exporting destination countries of each prefecture/city in our sample based on prefecture-level exporting data in 2000 in China Customs database. We then construct the weighted sum of total value of imports from the whole China of the top-5 exporting destinations of a given prefecture. We construct weights using the value of exports to these 5 countries from the city in 2000. The three-year average $PM_{2.5}$ is based on the levels of $PM_{2.5}$ in the current year and the past two years. Mortality rate is the all-cause mortality rate.

unadjusted mortality differences that contain a good deal of noise, so patterns are suggestive at best. Mortality rates decreased over time, hinting at possible endogeneity and bias from OLS estimates, as the general trends in economic development (increasing) and mortality (decreasing) might bias estimates toward zero. Both panels show counties with the smallest average relative increase in

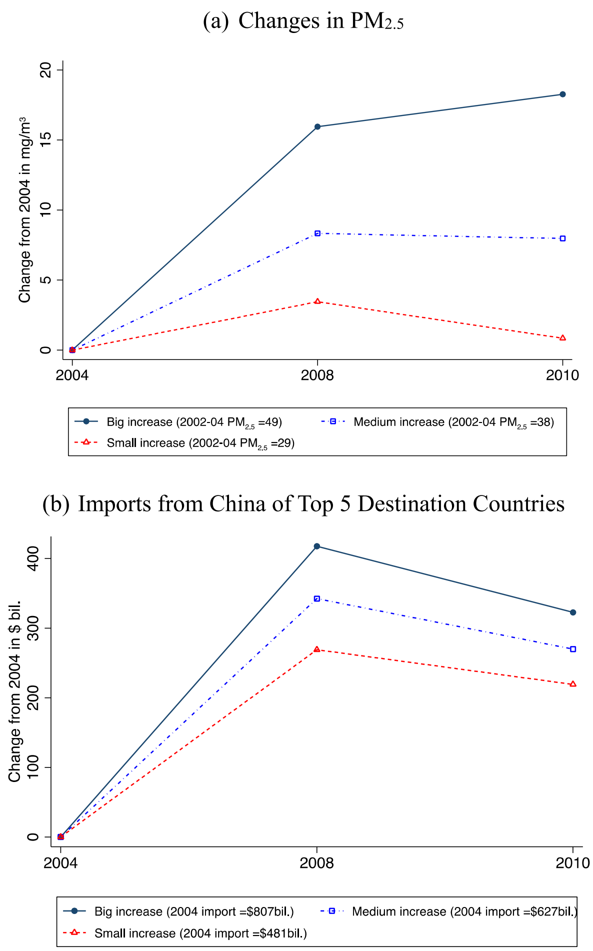


Fig. 3. Changes in $PM_{2.5}$ and Imports for Three Groups during 2004–2010 (a) Changes in $PM_{2.5}$
Note: Figures show the change in $PM_{2.5}$ (panel A) and international Chinese import demand (panel B), relative to 2004, by 2004–2010 changes in $PM_{2.5}$. The "Big increase" group consists of counties with the biggest increase in $PM_{2.5}$ concentration (75th percentile and above), with an average $PM_{2.5}$ concentration increase of 14.36 μg/m^3. The "Small increase" group consists of counties with the smallest increase (25th percentile and below), with an average $PM_{2.5}$ concentration increase of 2.89 μg/m^3. The "Medium increase" group is composed of all other counties (25th −75th percentile), with an average $PM_{2.5}$ concentration increase of 8.65 μg/m^3.

$PM_{2.5}$ concentration had the largest relative decline both in all-cause and respiratory mortality. In Panel (a), all-cause mortality declined more for the "Big increase" group than the "Medium increase" group, while for respiratory mortality the "Big increase" group declined less rapidly than the "Medium increase" group. The different trends of these two categories of mortality may be a result of particulate air pollution playing a larger role in respiratory than all-cause mortality (Pope et al., 1995).

To further illustrate the basic correlation between $PM_{2.5}$ and mortality, Fig. 5 presents residualized plots showing the relationship between the residualized mortality rate and the residualized $PM_{2.5}$, conditional on socio-economic conditions, weather variables and county-year-age-gender fixed effects. Panel (a) is for all-cause mortality of all ages while Panel (b) is for cardiorespiratory mortality of those ages 65 and above. The plots suggest a positive relationship between the mortality rate and ambient $PM_{2.5}$ levels, and the relationship is even stronger for the cardiorespiratory mortality among the elderly. However, OLS estimates may be subject to endogeneity and we use the IV method to identify the causal effect.

2.4. Instrumental variable construction

Our IV leverages the fact that demand shocks from the same destination countries could have different effects on the production centers across Chinese prefectures, depending on local trade intensity. Our first local trade variable is a measure of export intensity from each prefecture located upwind of each of the 161 counties/city districts in our data, using the year 2000 (the baseline year, the starting point of our trade data). This serves as the baseline year to capture variation in economic susceptibility of each prefecture to China-wide economic shocks from different export destinations, where different prefectures have different levels of exposure to international markets. It also generates variation in local economic susceptibility of prefectures to shocks from their export destinations,

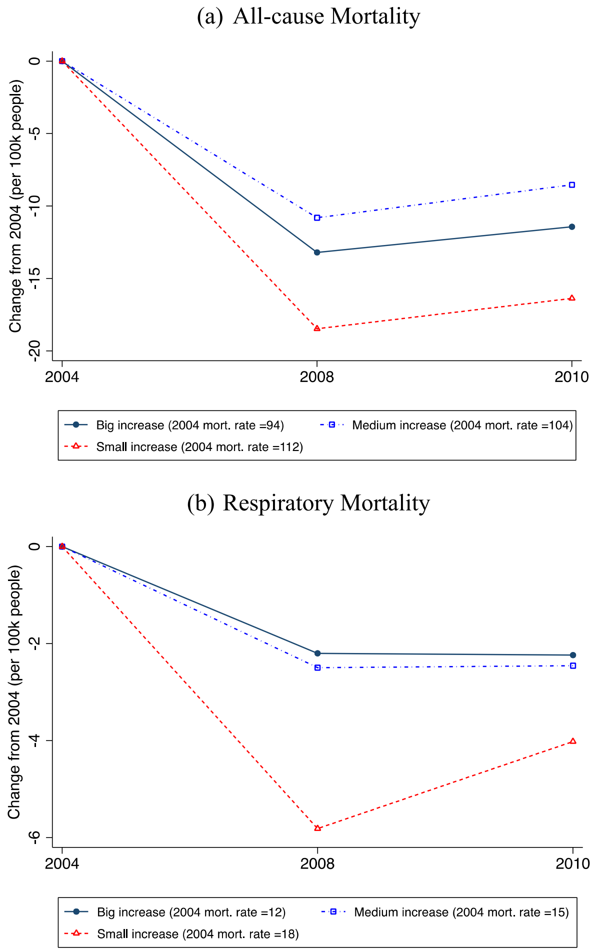


Fig. 4. Mortality rate by change in $PM_{2.5}$ (2004–2010) (a) All-cause Mortality
Note: Panel (a) shows the all-cause mortality rate (per 100,000 people) and Panel (b) shows the mortality rate due to respiratory diseases (per 100,000). The three lines are for the three groups of cities based on the change of $PM_{2.5}$ from 2004 to 2010. The "Big increase" group consists of counties with the biggest increase in $PM_{2.5}$ concentration (75th percentile and above), with an average $PM_{2.5}$ concentration increase of 14.36 μg/m^3. The "Small increase" group consists of counties with the smallest increase (25th percentile and below), with an average $PM_{2.5}$ concentration increase of 2.89 μg/m^3. The "Medium increase" group is composed of all other counties (25th −75th percentile), with an average $PM_{2.5}$ concentration increase of 8.65 μg/m^3.

as prefectures whose economies having higher dependence on export in the baseline year may be hit more by demand shocks from the export destinations than those relying less on export.

The second variable measures total annual export to each of the prefecture export destinations from China. We identify the top five export destination countries/regions for each prefecture in 2000, and then collect information on total Chinese exports to each of destinations in each year from 2001 to 2010. This captures differential demand shocks from export destinations. To generate the local demand shock, we use a weighted sum of national exports from China to the top five destinations, establishing weights for each prefecture using its specific top five exporting destination countries. Weights are the total exports of a given prefecture to each of the five destination countries, giving a higher weight to the demand shock from a country that historically imported more from the prefecture. For consistency with our pollution exposure variable, we generate a three-year average for the imports for 2004, 2008, and 2010 (e.g., values from 2004 are an average of 2002, 2003, and 2004).

The trade data show that accounting for top five destination countries/regions for all relevant prefectures yields 88 countries in total. Japan, the United States, Hong Kong, South Korea and Germany are the five countries/regions most frequently appearing as top destinations, and Southeast Asian countries such as Indonesia, Vietnam, Cambodia and Vietnam are among the 15 most frequent. Kuwait, the United States, Hong Kong, Japan and Libya are the five countries/regions with the largest trading volume with prefectures in China in 2000, followed by Singapore, German, Macao, Hungary and Sri Lanka. Many of these areas were hit differently by the 2008 global financial crisis, providing prefecture-level variations differences in import demand shocks, and thus differences in local pollution by prefecture.

As an example of our calculation method, consider a sample location (e.g., a county) *i* which has two prefectures, *a* and *b*, located

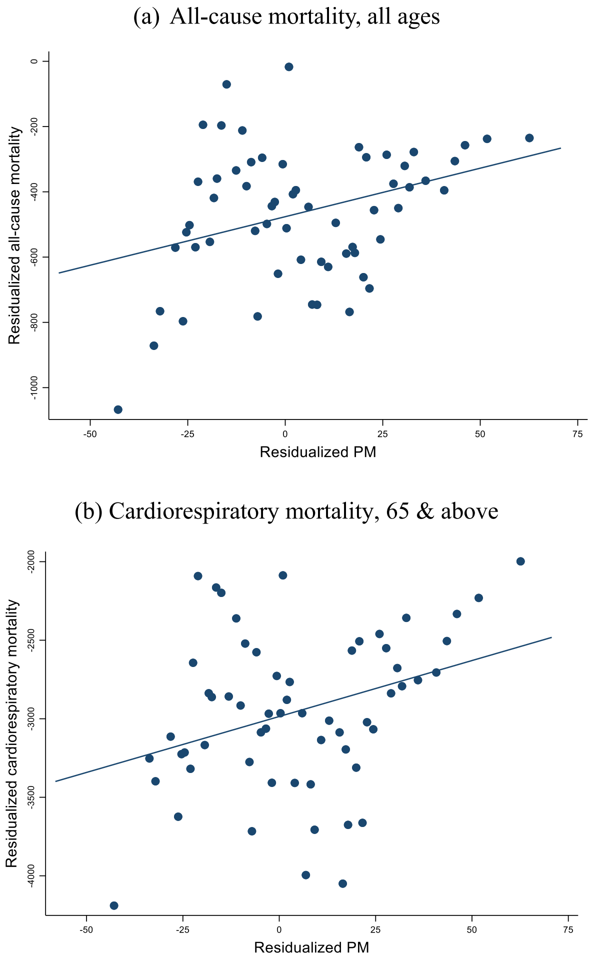


Fig. 5. Residualized plot of mortality against PM $_{2.5}$ (a) All-cause mortality, all ages
Note: Panel (a) shows the binned scatter plot of residualized all-cause mortality rate (in 100,000 people) against residualized PM $_{2.5}$ and Panel (b) shows the residualized cardiorespiratory mortality rate (in 100,000 people) against residualized PM $_{2.5}$. Each dot denotes the in-group average residuals, partialing out year FEs, county-gender-age FE, socio-economic controls (GDP per capita, population density, government expenditure, hospital beds, employment) and weather controls (temperature, precipitation, humidity, wind speed).

upwind. The top five export destination countries/regions for *Prefecture a* are 1, 2, 3, 4 and 5. The top five export destination countries/regions for *Prefecture b* are 6, 7, 8, 9, and 10. Let $China_X^Y$ represent the China-wide total exports to country/region X in year y, a_X^{2000} represent the year 2000 exports for *Prefecture a* to country X, and b_X^{2000} represent the year 2000 exports for *Prefecture b* to destination country X. Then the instrument value for sample location i in year Y would be:

$$upwindexport_{i,2000} \times top5upwind_{i,t} = \Sigma\left(a_X^{2000} * China_X^Y\right)_{X=1}^{5} + \Sigma\left(b_X^{2000} * China_X^Y\right)_{X=6}^{10}. \tag{1}$$

To better control for subpopulation baseline mortality differences, we separate all of our observations into county-age-gender-year cells. Each observation in a given county-year shares the same pollution and IV measures.

3. The empirical framework

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

$$y_{i,a,g,t} = \alpha \times pm_{it} + x_{it} \times \beta + \mu_t + \delta_i + \varepsilon_{it}, \tag{2}$$

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

A key empirical challenge in identifying the impact of $PM_{2.5}$ on mortality is the potential endogeneity of $PM_{2.5}$ from unobservables and measurement error. As Figs. 1 and 2 illustrate, while in general pollution levels increased in our data period across most counties in our sample, mortality rates decreased, highlighting the importance of controlling for evolving economic and social conditions. In addition, our $PM_{2.5}$ data are derived from the satellite AOD measures,[11] and measurement errors can arise when translating the satellite data to ground level $PM_{2.5}$ concentrations through a combination of estimation models, spatial extrapolation methods, and heterogeneous exposure around averages. If measurement error is uncorrelated with the true value, one can anticipate OLS estimates are subject to attenuation bias.

The other potential identification challenge is that inter-county/prefecture migration might be affected by pollution levels due to sorting and could in turn affect mortality rate. For example, if those who are affected the most by pollution moved out of highly polluted areas, it would bias the mortality impact of pollution toward zero. However, there are two reasons that our results are unlikely to be driven by migration during our data period. First, in the Chinese context, the Hukou (i.e. household registration) system means access to many public services such as education and medical care is a function of generally remaining in one's city of birth. This raises the costs of internal migration and limits mobility from one county to another., especially among those 65 and above for whom our estimated pollution impact is the strongest. Khanna et al. (2021) and Chen et al. (2022) both show that pollution can impact location decisions in China, but largely via movement of more educated and skilled workers earlier in their careers. This may explain why we find limited effects for the working age population in our context. Second, there was a lack of public information on air pollution and people's awareness of air pollution and their health impact was limited before 2013 as documented in Barwick et al. (2019). Nevertheless, we examine internal migration using 2005 Population Census (1% sample). Specially, we calculate the county-level share of residents whose Hukou is in a different county by age group and by health condition and find that the average share is less than 7.5% in the 161 sample counties, and only 2.7% for those 65 and above.

The following model shows the specification for the first-stage regression:

$$pm_{it} = \gamma \times upwindexport_{i,2000} \times top5upwind_{it} + x_{it} \times \theta + \omega_t + \eta_i + \zeta_{it}, \tag{3}$$

where i denotes county i and t denotes a year. pm denotes the three-year (t, t-1, and t-2) average of $PM_{2.5}$ concentration. $upwindexport_{i,2000}$ is the total export of upwind prefectures located within a radius of 300 km (henceforth upwind prefectures) of a given county i in 2000. $top5upwind_{it}$ is the total China-wide export to top-5 destination countries of upwind prefectures of a given county i in years t, t-1, and t-2. The interaction term of $upwindexport_{i,2000} \times top5upwind_{it}$ represents the trade shocks faced by upwind prefectures and serves as our IV for pm_{it}. x_{it} is a vector of the three-year averages of control variables including weather conditions and socioeconomic variables as defined in equation (2). ω_t is year fixed effects, and η_i county fixed effects. Appendix Fig. 1 presents the residualized plot which shows a positive relationship between the $PM_{2.5}$ level and the trade shocks faced by upwind prefectures. The relationship is stronger for trade shock to high-export upwind prefectures than to low-export upwind prefectures.

As discussed earlier, our IV strategy leverages both cross-sectional variation in export intensity in upwind prefectures in the baseline year (2000) and yearly variation in total exports to destinations/regions from China to allow demand shocks from the global economic recession to have differential impacts on $PM_{2.5}$ pollution across origin counties.[12] An identifying assumption is that demand shocks for export destinations affect health outcomes of any given county only through impacts on $PM_{2.5}$ levels. There are two concerns regarding the validity of the assumption. First, demand shocks in export destinations could affect local economic conditions, which in turn affect health outcomes. We address this in two ways. We control for a rich set of social and economic variables in our model. Results show that, in both in the first and second stages, including local socio-economic variables does not change the coefficients of interest, implying those potential confounders are unlikely to be a threat to identification. We also use shocks to nearby counties instead of the country of interest, as there is no clear reason to expect economic development in upwind counties to directly impact exclusively downwind counties except via pollution.

As a second concern, given the importance of China in the export market, the economic downturn in destination countries could be the result of supply shocks in China rather than demand shocks. Here we note that the generally accepted view is that the global economic recession in the late 2000s was initially caused by the bust of the housing market bubble in the United States, which led to financial and economic crisis across many countries. During this time, China's local economy grew steadily as discussed earlier (see Fig. 2) and did not enter recession, and played a positive role in world economic recovery.[13,14]

[11] Measurement error could also exist when using data from ground-level monitoring stations due to the issue of coverage, leading to attenuation bias, see for example Janke et al. (2009).

[12] The IV also leverages temporal and cross-sectional variations in demand shocks due to the cross-market variation in import exposure across localities in the spirit of Autor et al. (2013). Similarly, Chay and Greenstone (2003) use substantial pollution variation across US counties from a 1981–1982 recession to study the mortality impact of air pollution. Our research builds on the logic in these studies, using external demand shocks that propagate through trade to generate exogenous variation in local air pollution in China.

[13] 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.

[14] This presents a potential identification complication, as local economic activity can drive both pollution and other factors that influence health. To some extent, our set of economic controls helps address the effect of trade shocks on local economic conditions independent of pollution. Recall, however, that the instrumental variable for a given a county uses shifts in import demand from upwind surrounding areas but excluding the specific county.

4. Empirical results

4.1. p.m.$_{2.5}$ concentration and all-cause mortality

We begin with a model using the mortality rate (deaths per 100,000 people) as the dependent variable. The key regressor is the three-year average $PM_{2.5}$ concentration, which serves as our measure of long-term pollution exposure. We weight all regressions by county-age group population and cluster the standard errors at the county level.[15]

Table 2 presents regression results for six specifications. We begin with OLS estimates in column (1), a pooled cross-sectional OLS model including county-age-group-gender fixed effects and year fixed effects. These fixed effects address unobserved time-invariant determinants of mortality by region and demographic group, as well as common shocks in all counties across years, such as changes in national health care policies. Column (2) adds rich weather controls. Column (3) further adds socio-economic controls. Results in columns (1)–(3) show a positive but statistically insignificant relationship between long-term exposure to $PM_{2.5}$ and all-cause mortality. A 10 μg/m^3 increase in average (three-year) regular $PM_{2.5}$ exposure (approximately 40% of one standard deviation) raises mortality rates by 1% (approximately 0.5% of one standard deviation), with a standard error of 1.7.

Columns (4)–(6) in Table 2 repeat these three setups using our IV model. All three regressions show a positive effect larger than OLS estimates, and are statistically significant at 5% and above. The coefficient on $PM_{2.5}$ from our preferred specification in column (6), including controls, time fixed effects, and location/subgroup fixed effects, is 19.9, an order of magnitude larger than the corresponding OLS estimate in column (3), and statistically significant at the 1% level with a standard error of 6.8. This suggests a 10 μg/m^3 increase in the long-term exposure to $PM_{2.5}$ would lead to an approximate 20% increase in all-cause mortality. Our first-stage is strong enough by conventional measures for second-stage inference: the last row of Table 2 shows the F-statistics on the IV from the first-stage,[16] which range from 16 to 18 (Appendix Table 1 shows our full first-stage results).

The large difference between OLS and IV methods is common in recent economic literature using quasi-experimental methods to identify the causal effect of air pollution on health (Knittel et al., 2015; Schlenker and Walker, 2015), including research in China (Ebenstein et al., 2017). Columns (4) to (6) in Table 2 show coefficient estimates are consistent across different control specifications, which suggests instrument effects are unlikely to be a result of a common non-pollution channels (e.g., income). Specifically, the difference between the estimate in the specification without socio-economic controls (column 5) and that with those controls (column 6) is quite small (approximately 22 vs. 20).

To place our findings in context, we consider comparable estimates of pollution and mortality in China from the economics literature. Most closely related is Ebenstein et al. (2017), which studies the causal effect of long-term exposure to PM_{10} in Northern China using a RD 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 μg/m^3 of PM_{10}, is about one-half the size of our IV estimates for $PM_{2.5}$. These two estimates are quite similar once we factor in that $PM_{2.5}$ is a subset of PM_{10} – based on ground-level monitoring data in China which reports both $PM_{2.5}$ and PM_{10} during 2013–2018, a 1-unit increase in $PM_{2.5}$ corresponds to a 1.8-unit increase in PM_{10}.[17] It is encouraging for prior estimate validity that our analysis, based on an alternate source of variation and identification strategy, reinforces earlier results in the literature.

As another point of reference for the comparison of particle pollutants of different size, Chen et al. (2013) find a 10 μg/m^3 increase in total suspended particulates (TSP), which includes $PM_{2.5}$ and PM_{10}, increased mortality rates by 1.4%. The results from Chen et a. (2013) and Ebenstein et al. (2017) that use the same identification strategy suggest the impact of PM_{10} is approximately seven 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 epidemiological 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 3 shows results from various other pollution and health studies in epidemiology and economics, including some from OECD nations.

4.2. Robustness checks

We base some variation in our instrument on differences in prefecture-level export intensity in the baseline period of 2000. This

[15] Counties involved in our study are spatially dispersed with an average distance of 1390 km and a maximum distance of 4558 km. However, one might be concerned that counties which are close to each other and located within the same prefecture or the same province may be spatially correlated in terms of air pollution or mortality rate. To address this, we run regressions using two alternative ways of clustering the standard errors, i.e. clustered at the prefecture level and at the province level. Results show no significant difference among three alternative ways of clustering standard errors, further implying that the potential spatial correlation does not compromise the inference.

[16] Two upwind prefectures with the same level of export may have different environmental implications due to the differences in pollution intensity across exported products. To examine this, we generate an interaction term of the original IV with the share of the dirty output (i.e., from nine 2-digit industries considered being heavily polluting in terms of air pollution) in total output in upwind prefectures as an additional IV. In our original model with one IV, the Stock-Yogo test statistics (10% maximal value) is 18.27 while the Stock-Yogo test statistics (10% maximal value) of the model with the interaction term is 19.39, showing that adding the interaction term leads to a slightly stronger first stage. However, the estimated coefficient with two IVs is not quantitatively different in magnitude (see both results for models with two IVs in Appendix Table 2). Therefore, we proceed with one IV in our main analyses.

[17] The average daily concentrations of $PM_{2.5}$ and PM_{10} were 48 μg/m^3 and 86 μg/m^3 at the national level during 2013–2018 based on ground-level monitoring stations.

Table 2
The impact of $PM_{2.5}$ on all-cause mortality.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5	1.042	1.134	1.085	17.099**	22.228***	19.902***
	(1.579)	(1.654)	(1.734)	(6.661)	(7.575)	(6.811)
ln(GDP per capita)			3.478			−36.851
			(56.920)			(61.356)
ln(population density)			65.796*			65.148*
			(37.418)			(34.850)
ln(government spending)			21.434			−29.622
			(65.499)			(81.562)
ln(hospital beds)			11.064			−13.673
			(62.853)			(72.596)
ln(employment)			28.295			45.812
			(20.574)			(34.032)
Precipitation		−0.001	0.033		0.199	0.180
		(0.245)	(0.241)		(0.311)	(0.288)
Humidity		0.015	0.412		2.783	2.468
		(4.558)	(4.449)		(5.844)	(5.450)
Wind speed		29.546	27.894		2.601	6.808
		(38.300)	(37.186)		(47.299)	(43.462)
Temperature($\leq$ 40)		0.733	0.893		7.148	5.469
		(3.273)	(3.277)		(5.850)	(5.108)
Temperature (40–60 F)		0.621	1.070		3.795	2.943
		(1.971)	(1.990)		(3.028)	(2.633)
Temperature (80–90 F)		−0.316	−0.550		−3.734	−4.016
		(1.992)	(1.999)		(2.785)	(2.623)
Temperature ($\geq$ 90 F)		6.910	5.982		5.809	6.502
		(6.374)	(6.590)		(8.739)	(8.584)
County-age-gender FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
First-stage F-statistics (p-values)	–	–	–	17.40 (0.0001)	16.23 (0.0001)	18.27 (0.0000)
No. of observations	4809	4809	4809	4809	4809	4809

Note: The dependent variable is deaths per 100,000 people; $PM_{2.5}$ are past three-year mean $PM_{2.5}$ concentration serving as a proxy for long-term exposure to $PM_{2.5}$; the reference group for temperature bins is 60–80 F *, ** and *** are significance levels at 1%, 5% and 10%, respectively. Standard errors clustered at the county level are in parenthesis. Column (1) is a pooled cross-sectional OLS model including county-age-group-gender fixed effects and year fixed effects, column (2) adds weather controls, and column (3) adds socio-economic controls. Columns (4)–(6) are 2SLS results corresponding to columns (1)–(3), where we instrument for pollution levels using shifts in global demand for Chinese exports by region – Section 2.4 describes instrument construction in detail.

would be problematic if upwind prefectures have differential effects on both pollution and mortality in downwind counties over time due to productivity or supply changes unrelated to import shocks, which could cause differential background trends in mortality correlated with, but not causally related to, emissions. To test for this, we include an interacted time trend with export intensity in the prefecture baseline period (2000) as an additional control variable. We present results for both stages including the interaction term in the Appendix Table 4. The interaction term is not statistically significant in the first stage, and the inclusion in the second stage does not change the economic or statistical significance of our main results.

$PM_{2.5}$ particles are light, can travel at a speed of 10 mph, and often reside in the atmosphere for 3–4 days (Díaz and Dominguez, 2009; Yassin et al., 2012). Their region of influence is determined by wind speed and direction. Based on atmospheric modeling, Zhang et al. (2015) and Wang et al. (2019) document significant regional pollutant transport in China. For example, nearly half of the pollution in Beijing originates from sources outside of the municipality. 300 km is within the distance for the long-range transport nature of $PM_{2.5}$ to manifest as shown in the science literature. For example, at a moderate speed of 15 miles per hour, it takes only one day for $PM_{2.5}$ from 360 miles away to be transported. $PM_{2.5}$ can travel over 1000 miles from the ground level within two days from northern to southern China driven by cold surges (Wang et al., 2017). Nevertheless, concerns may still raise for our choice of 300 km radius to determine upwind prefectures. We conduct robustness checks using two alternative cut-off points, 200 km and 400 km, as the radius to determine the upwind prefectures and identify the causal effect on all-cause, cardiorespiratory and cardiovascular mortality. Table 3 presents results for all three cut-off points, and shows that using the two alternative cut-off points generates quantitatively the same results as those using 300 km.

Our IV design leverages wind transport of pollution from upwind prefectures, which were subject to trade shocks from their corresponding export destinations. However, it could be that wind direction is not a causal factor in pollution contribution, but rather simple proximity, which would raise questions of local economic spillovers. To further examine the validity of our IV, we conduct a placebo test in which we create "fake" upwind prefectures in our first stage by reshuffling the prefectures in our original data set. If our instrument captures pollution transport as intended rather than other factors (e.g., geographic proximity), we expect the placebo analysis with the "fake" upwind prefectures to generate less statistically and economically significant estimates. We repeat the analyses for 500 iterations, using the main model specification in the column (6) of Table 2. Fig. 6 presents the histograms of the first-stage F-

Table 3
Upwind prefectures within varied distance.

	All-cause	Cardiorespiratory	Cardiovascular
Panel A: Upwind within 300 km			
PM2.5	19.902***	12.171***	9.802***
	(6.114)	(2.974)	(2.565)
All other controls	YES	YES	YES
County-age-gender FE	YES	YES	YES
Year FE	YES	YES	YES
First-stage F-statistics (p-values)	17.55 (0.0001)	174.56 (0.0000)	174.56 (0.0000)
No. of observations	4809	4809	4809
Panel B: Upwind within 400 km			
PM2.5	20.595***	12.917***	10.208***
	(4.034)	(2.864)	(2.546)
All other controls	YES	YES	YES
County-age-gender FE	YES	YES	YES
Year FE	YES	YES	YES
First-stage F-statistics (p-values)	16.44 (0.0001)	174.29 (0.0000)	174.29 (0.0000)
No. of observations	4881	4881	4881
Panel C: Upwind within 200 km			
PM2.5	16.100***	9.699***	7.405***
	(4.105)	(2.828)	(2.122)
All other controls	YES	YES	YES
County-age-gender FE	YES	YES	YES
Year FE	YES	YES	YES
First-stage F-statistics (p-values)	17.27 (0.0001)	227.90 (0.0000)	227.90 (0.0000)
No. of observations	4741	4741	4741

Note: The dependent variable is deaths per 100,000 people; $PM_{2.5}$ are past three-year mean $PM_{2.5}$ concentration serving as a proxy for long-term exposure to $PM_{2.5}$; the reference group for temperature bins is 60–80 F *, ** and *** are significance levels at 1%, 5% and 10%, respectively. Standard errors clustered at the county level are in parenthesis. Column 1 in Panel A replicates our primary results from Column 6 of Table 2, using 300 km as a cut-off point for the radius to determine the upwind prefectures/cities. Panels B and C use alternate distances of 400 km and 200 km, respectively, as cut-off points. Columns 2 and 3 repeat the analysis using more specific cause of death outcomes, with cardiorespiratory deaths in column 2 and cardiovascular deaths in column 3.

statistics and p-values for the estimated coefficient of $PM_{2.5}$. Recall in the column (6) of Table 2 discussed earlier, we have a value of 18.27 for the first-stage F-statistics and an estimated coefficient with a magnitude of 19.902 and a 1% statistical significance level. Only 10 out of these 500 iterations have an F-statistics greater than 10 and only 1 iteration has an F-statistic greater than 18.27 (the first-stage F-statistic in our original model); only 16 out of 500 iterations have a p-value less than 10%. This shows that using randomly selected nearby prefectures as pollution origin locations yields weak IVs in the first stage, and a statistically insignificant estimated coefficient of the $PM_{2.5}$ in the second stage. The placebo test lends further support of our identification strategy using wind transport to generate exogenous pollution variation.

4.3. *Heterogeneity across demographic groups*

Recent studies recognize health impacts of air pollution differ across population groups with different characteristics such as age and gender (Schlenker and Walker, 2015; Clougherty, 2010; Zhou et al., 2015; Dockery et al., 1993), and that the elderly and children are particularly vulnerable to the exposure to pollution (WHO, 2016; Brook et al., 2010). Epidemiologic studies show a strong link between cardiorespiratory health and long-term exposure to $PM_{2.5}$ (e.g., Pope et al., 1995, 2002, 2004; WHO, 2016; Dockery et al., 1993; Lim et al., 2012), and increasing evidence shows the largest portion of ambient $PM_{2.5}$–induced deaths are related to cardiovascular disease (Brook et al., 2010; Brook et al., 2010). To see if such effects appear in our data, we analyze results by age groups in terms of all-cause mortality and cardiorespiratory mortality (i.e., mortality due to cardiovascular and respiratory). For all subgroup analysis we focus on our IV results.

Table 4 shows results by age groups (Appendix Table 5 shows first-stage results). Panels A and B show suggestive evidence health effects of $PM_{2.5}$ pollution vary across age groups. For the full sample, results are statistically significant at conventional levels for all-cause, cardiorespiratory and cardiovascular mortality (column 2, Table 4). Among age groups, the coefficients of all-cause, cardiorespiratory and cardiovascular mortality are statistically significant and largest for the age 65 and above group (last column, Table 4), aligning with the above literature finding the elderly are most vulnerable. For the age group below 20, we do not observe statistically significant health effects. This might be because our data does not allow us to separate infants from more robust young adult groups, unlike existing literature on infants (e.g., Chay and Greenstone, 2003). To examine the sensitivity of our results to outcome specification, we also run additional regressions using the log-linear form for all-cause, cardiorespiratory and cardiovascular mortality by age groups. Appendix Table 6 presents estimation results, where the elderly group remains most vulnerable group among all age groups, consistent with results from the linear-linear specifications.

We next repeat the analysis, separating results by gender rather than age group. Table 5 shows the estimation results (Appendix Table 7 shows the first-stage results). Coefficient magnitudes suggest $PM_{2.5}$ pollution has a slightly stronger effect on

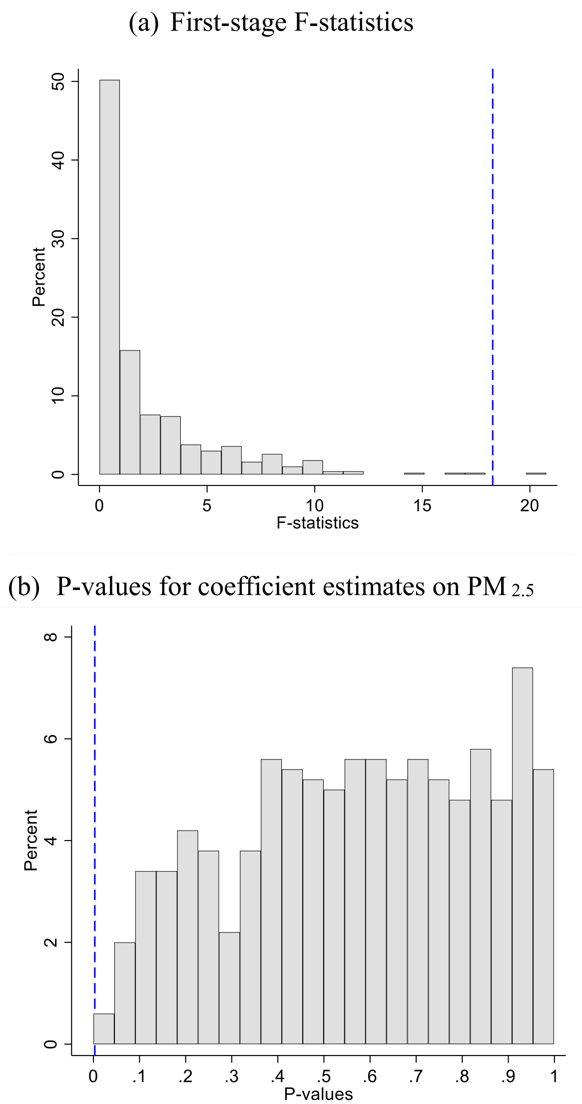


Fig. 6. Results from Placebo tests (a) First-stage F-statistics
Note: Figures shows the histograms based on outcomes of 500 iterations of placebo tests for our first (panel A) and second (panel b) stage estimates. In each interation, we randomly assign "upwind" prefectures for a given sample county, and rebuild our instrument based on the randomized data. Panel A plots the F-statistics from the first stage of each of the 500 tests. Panel b plots the p-values of the second stage estimates. Dashed vertical lines in (a) and (b) are the first-stage F-statistics (18.27) and p-values (0.003) of the estimated coefficients of $PM_{2.5}$, respectively, from our main results. In placebo tests, only 10 out 500 iterations have an F-statistics greater than 10 and only one iteration has an F-statistics greater than 18.27; only 16 out of 500 iterations have a p-value less than 10%.

females than on males in terms of all-cause mortality (at 5% significance level) and cardiorespiratory mortality (at 10% significance level) but no significant gender difference for cardiovascular mortality. The existing literature on the health impact of air pollution have not provided a consensus on the gender differences (see a review by Clougherty (2010)). While our finding is consistent with the finding by Kan et al. (2008) that air pollution has stronger effects on respiratory mortality among females than males, we note that none of the differences are large enough such that subgroup estimates are statistically different from each other.

4.4. The shape of the dose-response function

Given the lack of data and rigorous empirical evidence on the health impacts of air pollution in developing countries, literature often relies 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 The World Bank, 2007). However, the level of concentration in developing countries is often outside the range observed in developed countries (Brook et al., 2010). Discussions in the epidemiological literature

Table 4
The effect of $PM_{2.5}$ on mortality by age.

	All ages	Below 20	[20, 65)	65 & above
Panel A: all-cause mortality				
$PM_{2.5}$	19.902***	2.113*	4.908*	196.852***
	(6.811)	(1.257)	(2.718)	(63.539)
No. of observations	4809	1577	2424	808
Panel B: Cardiorespiratory mortality				
$PM_{2.5}$	12.171***	0.281	1.397	136.569***
	(4.377)	(0.307)	(0.920)	(46.752)
No. of observations	4809	1577	2424	808
Panel C: Cardiovascular mortality				
$PM_{2.5}$	9.802***	−0.043	0.719	108.634***
	(3.512)	(0.088)	(0.760)	(36.743)
No. of observations	4809	1577	2424	808
First-stage F-statistics (p-values)	18.27 (0.001)	17.56 (0.000)	18.11 (0.000)	17.45 (0.001)

Note: The dependent variable is deaths per 100,000 people. $PM_{2.5}$ are past three-year mean $PM_{2.5}$ concentration serving as a proxy for long-term exposure to $PM_{2.5}$. All regressions control for socio-economic and weather controls, year FE, county-age-gender FE or county-gender FE as in column 6 of Table 2. *, ** and *** are significance levels at 1%, 5% and 10%, respectively. Standard errors clustered at the county levels are in parenthesis.

Table 5
The effect of $PM_{2.5}$ on mortality by gender.

	linear-linear		log-linear	
	Male	Female	Male	Female
Panel A: All-cause mortality				
$PM_{2.5}$	19.698***	20.128***	0.021*	0.030**
	(7.280)	(6.624)	(0.012)	(0.015)
No. of observations	2416	2393	2416	2393
Panel B: Cardiorespiratory mortality				
$PM_{2.5}$	11.472***	12.888***	0.015	0.026*
	(4.454)	(4.474)	(0.015)	(0.016)
No. of observations	2416	2393	2416	2393
Panel C: Cardiovascular mortality				
$PM_{2.5}$	8.777**	10.863***	0.015	0.018
	(3.434)	(3.745)	(0.014)	(0.016)
No. of observations	2416	2393	2416	2393
First-stage F-statistics (p-values)	18.27 (0.001)	17.56 (0.000)	18.12 (0.000)	17.45 (0.001)

Note: The dependent variable in columns (1) & (2) are deaths per 100,000 people and the dependent variable in columns (3) & (4) is log-transformed deaths per 100,000 people. $PM_{2.5}$ are past three-year average $PM_{2.5}$ concentration serving as a proxy for long-term exposure to $PM_{2.5}$. All regressions control for socio-economic and weather controls, year FE, county-age-gender FE or county-gender FE as in column 6 of Table 2. *, ** and *** are significance levels at 1%, 5% and 10%, respectively. Standard errors are clustered at the county level are in parenthesis.

suggest that the shape of the dose-response function a steeper slope at lower concentration level than at higher concentration level (e.g. Schwartz and Marcus, 1990; Pope and Dockery, 2006; Pope et al., 2009). Whether the dose-response function exhibits nonlinearity is critical for conducting credible out-of-sample predictions, estimating the marginal health costs of pollution and understanding optimal levels of regulation. Given the potential endogeneity issues discussed earlier, for the spline regression analysis, we focus on the results from the IV estimation.

An advantage of our study is the rich variation in pollution levels across time and space in China, allowing for consideration of the dose-response shape. Ideally, we would trace out the shape of the dose-response function across many levels, possibly through nonlinear estimates or a linear spline with many break points. However, in our IV framework, each additional indicator or knot in the spline generates another potentially endogenous variable and places greater weight on the estimation. 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 $\mu g/m^3$) (WHO, 2016). We then run linear spline regressions.

To generate additional instruments, we create three dummy variables based on terciles of $PM_{2.5}$ concentration (below the 33rd percentile, between the 33rd percentile and the 67th percentile, and above the 67th percentile). We then interact these three dummy variables with the basic IV and its square term to generated six IVs for spline regressions. Our intent is to increase the number of available instruments in a manner consistent with identifying effects at different levels of the distribution of pollution.[18]

[18] This could potentially violate the exclusion restriction if terciles of pollution levels correlate with the error term in the regression of pollution and mortality.

Similar to our main models, we conduct analyses for all-cause, cardiorespiratory and cardiovascular mortality by age groups.[19] Results in Table 6 show a consistent pattern that the marginal effects of pollution are lower for higher level of $PM_{2.5}$, and effects are economically significant for both higher and lower levels of pollution. For example, for all-cause mortality in the whole sample, the marginal effect of $PM_{2.5}$ at the lower concentration level is about 32 additional deaths per 100,000, which is approximately 1.9 times of the marginal effects at higher levels of 17 additional deaths per 100,000 (column 2, Panel A, Table 6). Similar patterns appear for cardiorespiratory and cardiovascular mortality, where the marginal effect of the pollution at the lower level is 1.78 and 1.75 times of that at the higher level, respectively (column 2 in Panel B and Panel C). This suggests a concave dose-response function, supporting recent results in Cohen et al. (2017), though the standard errors are large enough such that, while both portions of the spline are statistically different from zero, they overlap in their confidence intervals.

The elderly group remains the most vulnerable among all age groups, consistent with earlier results. Marginal effects are statistically and economically significant for both higher and lower levels of pollution. The marginal effect of the pollution at the lower level is 1.70, 1.74 and 1.69 times of that at the higher level, respectively (last column, Table 6).

The potential concavity of the dose-response function implies diminishing marginal effects of pollution on health. This suggests marginal returns to improving air quality are positive but lower when pollution levels are very high, which carries important implications for comparing studies across low-vs. high-pollution areas. Out-of-sample projections of health benefits from initial reductions in $PM_{2.5}$ in developing countries, based on the estimates at lower levels of concentration typically observed in developed countries, could lead to overestimation at the margin. However, this also implies higher pollution countries can expect increasing marginal returns to pollution reduction as they improve air quality.

Variation in the shape of the dose-response function may also help explain why some pollution-reduction programs in high-pollution areas initially see limited marginal improvements in health. For example, Greenstone et al. (2019) find 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 1000 live births).[20] They did not perform an IV analysis, but converting their reduced form result to an IV by dividing by their "first stage" gives a (noisy) marginal effect of 0.01 deaths per 1000 live births per unit of particulates. This is at a very high pre-policy TSP 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 1000 live births per unit of TSP, from a pollution baseline of approximately 70 $\mu g/m^3$ of TSPs.[21] Concavity of the dose-response function would suggest that while the India reductions in particulates had initially small marginal effects, they pushed the region toward a point of higher marginal returns from further reductions.

5. Conclusion

Using mortality data by age and gender from 161 representative counties in China in 2004, 2008 and 2010, we estimate the causal impact of long-term ambient $PM_{2.5}$ on mortality in the context of a modern developing economy. We identify effects using variation in pollution induced by demand shocks from destination countries consuming Chinese exports during the global economic crisis in the late 2000s. Demand shocks from areas across the globe filter through to local economies via reduced demand for goods, shifting export production, which then shifts local pollution levels for nearby regions via wind-based pollution transport. This can change local $PM_{2.5}$ concentration differently across counties in China due to: (1) differences in the exposure of the nearby economies to export, (2) variation in the demand shocks themselves, and (3) prevailing wind direction.

Our results suggest long-term exposure to higher $PM_{2.5}$ levels (measured as a rolling three-year average) leads to statistically and economically significant increases in cardiorespiratory and respiratory mortality, especially among individuals 65 years old and above. Our quasi-experimental estimates also show empirical evidence of a concave dose-response function: we find per-unit reductions in ambient $PM_{2.5}$ have up to 2 times the benefit at the lower (below the median in our data) levels of $PM_{2.5}$. This suggests caution when using the benefit transfer approach to infer the impacts 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.

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. To combat this challenge, Premier Li Keqiang declared "war on pollution" at the opening of the 2014 annual meeting of People's Congress, denouncing smog as "nature's warning against inefficient and blind development." China is taking aggressive approaches to reduce pollution and these actions will entail significant cost through technology adoption and transition to cleaner energy (Greenstone et al., 2021). Our study contributes to understanding health benefits from pollution reduction, a key component in the cost-benefit analysis of air pollution regulations in China, and also suggests China

[19] We also conduct analyses for all-cause, cardiorespiratory and cardiovascular mortality separately by gender, and find results similar to the gender differences in our main model. The coefficient estimates suggest PM2.5 pollution has a slightly stronger effect on females than on males, consistent with the finding in Kan et al. (2008), though differences are not such that subgroup estimates are statistically different from each other. We therefore do not include detailed discussions on gender differences of the spline regressions in the main text. Regression results are available upon requests.

[20] This estimate is based on the five-year results from Table 3 in Greenstone et al. (2019) for PM, and five-year results from Table 6 for infant mortality.

[21] We derive this estimate using the IV results from Table 4 in Chay and Greenstone (2003), which suggest mortality reductions of five fewer deaths per 100,000 live births per unit of TSP.

Table 6
Spline regressions (2SLS results).

	All ages	Below 20	[20, 65)	65 & above
Panel A: All-cause mortality				
$PM_{2.5}$ below 42 μg/m3	32.364*	1.326	13.038	301.719**
	(17.238)	(2.283)	(9.416)	(137.905)
$PM_{2.5}$ above 42 μg/m3	17.466***	1.365	3.939	176.584***
	(6.761)	(0.923)	(3.077)	(58.433)
Panel B: Cardiorespiratory mortality				
$PM_{2.5}$ below 42 μg/m3	22.349**	0.368	3.720	246.852**
	(10.817)	(0.581)	(2.563)	(106.525)
$PM_{2.5}$ above 42 μg/m3	12.569***	0.109	1.166	141.583***
	(4.401)	(0.273)	(0.982)	(43.610)
Panel C: Cardiovascular mortality				
$PM_{2.5}$ below 42 μg/m3	16.022**	0.343**	3.247	165.170**
	(8.035)	(0.160)	(1.975)	(79.072)
$PM_{2.5}$ above 42 μg/m3	9.145***	0.047	0.826	97.758***
	(3.393)	(0.074)	(0.819)	(32.437)
Panel D: First-stage statistics				
Angrist-Pischke F-statistics (p-values)				
$PM_{2.5}$ below 42 μg/m3	9.51	8.59	9.43	10.08
	(0.00)	(0.00)	(0.00)	(0.00)
$PM_{2.5}$ above 42 μg/m3	16.65	19.33	15.28	17.97
	(0.00)	(0.00)	(0.00)	(0.00)
Stock-Yogo critical values (10%)	9.48	9.48	9.48	9.48
No. of observations	4809	1577	2424	808

Note: The dependent variable is deaths per 100,000 people. All regressions control for socio-economic and weather controls, year FE, county-age-gender FE or county-gender FE as in column 6 of Table 2. *, ** and *** are significance levels at 1%, 5% and 10%, respectively. Standard errors clustered at the county level are in parenthesis. Panel A shows all-cause mortality, panel B shows cardiorespiratory mortality, and panel C shows cardiovascular mortality. Panel D shows the F-statistics and p-values for first stage regressions – Appendix Table 8 shows first-stage regressions in detail. Columns show results by age group. Regressions use a spline in pollution, with a knot point at the median (42 μg/m^3) of the $PM_{2.5}$ concentration as the cut-off point. In this regression, we interact our original instrument and it's square with terciles of pollution levels to generate additional instruments – see Section 5.4 for details.

could see increasing marginal benefits of pollution reduction as air quality improves.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102759.

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