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TRADE, POLLUTION AND MORTALITY IN CHINA

Matilde Bombardini
Bingjing Li

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ABSTRACT

Has the expansion in exports affected pollution and health outcomes across different prefectures in China in the two decades between 1990 and 2010? We exploit variation in the initial industrial composition to gauge the effect of export expansion due to the decline in tariffs faced by Chinese exporters. We construct two export shocks at the prefecture level: (i) *PollutionExportShock* represents the pollution content of export expansion and is measured in pounds of pollutants per worker; (ii) *ExportShock* measures export expansion in dollars per worker. The two measures differ because prefectures specialize in different products: while two prefectures may experience the same shock in dollar terms, the one specializing in the dirty sector has a larger *PollutionExportShock*. We instrument export shocks using the change in tariffs faced by Chinese producers exporting to the rest of the world. We find that the pollution content of export affected pollution and mortality. A one standard deviation increase in *PollutionExportShock* increases infant mortality by 2.2 deaths per thousand live births, which is about 13% of the standard deviation of infant mortality change during the period. The dollar value of export expansion tends to reduce mortality, but is not always statistically significant. We show that the channel through which exports affect mortality is pollution concentration: a one standard deviation increase in *PollutionExportShock* increases SO2 concentration by 5.4 micrograms per cubic meter (the average is around 60). We find a negative, but insignificant effect on pollution of the dollar-value export shocks, a potential "technique" effect whereby higher income drives demand for clean environment. We find that only infant mortality related to cardio-respiratory conditions responds to exports shocks, while deaths due to accidents and other causes are not affected.

Matilde Bombardini
Vancouver School of Economics
University of British Columbia
6000 Iona Drive
Vancouver, BC V6T 1L4
CANADA
and CIFAR and RCEA
and also NBER
matilde.bombardini@ubc.ca

Bingjing Li
National University of Singapore
bingjing.crystal@gmail.com

1 Introduction

Among the many extraordinary dimensions of China's economic growth in the last 3 decades is the contemporaneous spectacular boom in export performance: the annual export growth rate was 14% during the 1990s and 21% during the 2000s. At the same time, this rapid economic growth has been accompanied by concerns that many of the benefits deriving from higher incomes may be attenuated by the similarly rapid deterioration in the environment and increase in pollution. According to Ebenstein et al. (2015) many of the gains in health outcomes have been slowed down by a simultaneous rise in the concentration of pollutants. In this paper we study how the export boom in China between 1990 and 2010 affected pollution and infant mortality across different prefectures. We exploit variation across prefectures in the initial pattern of comparative advantage to build local export shocks. This is similar to the approach by Topalova (2010), Kovak (2013) and Autor et al. (2013) to study the effects of import competition on employment, with the important difference that here we are interested in the export demand shock generated by the rest of the world. We therefore build an instrument that captures the part of China's export increase that is predicted by the change in tariffs faced by Chinese exporters over time in different sectors.

Why are we interested in this specific component of output growth ? In general, production for both domestic consumption and exporting responds to a multitude of shocks. These include supply shifters, like productivity innovations and institutional changes, as well as demand-side shifters, each of which may affect emissions differently. Were we to simply consider the correlation between emissions and output, we would not be able to easily interpret it. We therefore focus on a specific dimension of aggregate demand where this identification problem is alleviated, by making use of the presence of externally imposed tariffs. We demonstrate how to construct an instrument that can isolate foreign demand shocks, orthogonally to other unobserved sources of output dynamics. Finally, to further motivate our focus on foreign demand shocks faced by China, let us restate that the period 1990-2010 is one of extraordinary integration of China in the world economy and is therefore a quantitatively important driver of global output growth, whose environmental consequences, we believe, are worth studying in their own right.

Our analysis relies on variation in export growth at the local level. Therefore the tariff-predicted export expansion at the national level is apportioned to the various prefectures according to initial sectoral employment shares. We construct two export shocks at the prefecture level: (i) $PollutionExportShock$ represents the pollution content of export expansion and is measured in pounds of pollutant per worker; (ii) $ExportShock$ measures the dollars per worker associated with export expansion. Both measures rely on initial industrial composition. The variable $ExportShock$ measures the extent to which a prefecture is initially specialized in industries that subsequently experience a large export increase. The variable $PollutionExportShock$ captures the interaction of export expansion and pollution intensity: prefectures with larger initial employment in industries that both experience large export shocks *and* have high emission intensity are expected to become more polluted. The two measures differ because prefectures specialize in different products and while two prefectures may experience the same export shock in dollar terms, the one specializing in a polluting sector, like steel, experiences a larger $PollutionExportShock$. Borrowing the language of Grossman and Krueger (1995) and Copeland and Taylor (2003), $PollutionExportShock$ captures a "scale" effect: prefectures that experience a larger increase in exports in dirty industries are expected to see their pollution increase. The variable $ExportShock$ measures an income effect: holding constant the implied total emissions due to increased exports, higher revenues from exports may result in lower pollution due to a "technique" effect by which demand for a clean environment rises with income.

How large are the effects we estimate? We find that a one standard deviation increase in $PollutionExportShock$ increases infant mortality by an additional 2.2 infant deaths per one thousand live births. The magnitude of this effect has to be gauged in the context of the evolution of infant mortality over this period. Between 1990 and 2010 infant mortality rate in China went from 36 per thousand to 5 deaths per thousand live births, but this decline hides substantial heterogeneity. Between 2000 and 2010 for example, the 75th percentile prefecture experienced a decline of 23.7 deaths, while the 25th percentile prefecture saw a drop of only 8.7. What our results imply is that increased pollution due to specialization and exports explains about 17% of this differential decline across different areas in China. Importantly, using the same data as Chen et al. (2013), we can show that such effects are concentrated on mortality due to cardio-respiratory conditions, which are supposedly the most sensitive to air pollution. On the contrary, mortality due to other causes does not respond to any of the export shocks. While we find a strong and consistent impact of $PollutionExportShock$ on mortality, the effect of $ExportShock$ is less robust. We find that $ExportShock$ tends to decrease mortality, but the effect is statistically significant only during the decade 2000-2010 (during which export expansion was an order of magnitude bigger than during the 1990's).

Why do $PollutionExportShock$ and $ExportShock$ affect mortality? The next question we tackle is the quantification of the channels through which these two shocks influence health outcomes. The most intuitive channel through which $PollutionExportShock$ affects mortality is pollutant concentration, while $ExportShock$ may affect mortality through different channels. On the one hand, an increase in income due to export expansion may increase the demand for clean environment and the consumption of healthcare services which would in turn improve health outcomes. On the other hand, it may also increase the consumption of environmentally unfriendly goods like cars, which would in turn raise pollution. Our identification relies on the assumption that conditional on $ExportShock$, $PollutionExportShock$ affects mortality only through the channel of air pollution. We show that a positive $PollutionExportShock$ increases the concentration of SO_2, while $ExportShock$ tends to reduce it. In the decade 2000-2010 a one standard deviation increase in $PollutionExportShock$ increases SO_2 concentration by 6.3 $\mu g/m^3$ while a one standard deviation increase in $ExportShock$ decreases SO_2 concentration by 1.9 $\mu g/m^3$, but this latter effect is not significant. These changes represent respectively 22.5% and −6.7% of the interquartile range, i.e. the difference between the 25th and 75th percentile prefectures in terms of SO_2 change during 2000-2010. We have two possibile explanations for the lack of a strong income effect of export expansion on both mortality and pollution. The first one has to do with the fact that environmental policy is set centrally in China and that local increases in income may not directly translate into local changes in policy (although they may affect enforcement).[1] The second potential explanation is based on other consequences of income growth that may be associated to increased pollution such as the increase in vehicle ownership (see Dargay et al. 2007).

Finally, we close the loop by showing how pollution affects infant mortality, a link which has been studied before, but for which we offer a different identification strategy. We find the elasticity of infant mortality to SO_2 to be 0.9, which is quantitatively similar to the estimate by Tanaka (2015) of 0.82 for China, albeit during a different time period. The elasticity of IMR to $PM2.5$ is 2.1, which is not directly comparable to the estimate of 1.73 we have for China by Chen et al. (2013) because the pollutant in that case is total suspended particles. A potential explanation of this larger effect is that $PM2.5$ is considered much more fatal due to the smaller diameter of the particles.

We are careful in addressing a series of issues that may affect confidence in these results. Importantly, like all studies employing a Bartik approach, our paper faces the challenge of showing that the results are not simply due to initial specialization. After all, it is plausible to hypothesize that prefectures initially specialized in dirty industries experience a relative increase in mortality over this period even without export shocks. We present a simple graphical way to cast aside this concern. Even though we present all data details later, we construct a measure that simply classifies sectors according to two criteria: dirty/clean (D and C) and high-export-growth/low-export-growth in the decade 2000-10 (H and L).[2] We then obtain employment shares in 2000 for each prefecture in each of the 4 groups of industries (CH, DH, CL and DL). Panel A of Figure 1 plots the change in infant mortality rate (IMR) for each prefecture in 2000-2010 against the following relative employment ratio in the year 2000:

$$\frac{EmpShare(DH)}{EmpShare(CH) + EmpShare(DH)} \, .$$

[1]See Hao et al. (2007) for a description of the national policies adopted over the last three decades.

[2]Dirty and Clean industries are grouped according to whether the sectoral value of emission intensity is above or below the median. The high-export-growth (low-export-growth) industries are the ones belonging to upper (bottom) tertile of export growth per worker. More details can be found in Appendix A.

Figure 1 shows that IMR increased in prefectures that initially had a relatively higher employment in dirty industries that *also* saw high export growth in 2000-10. Conversely, Panel B of Figure 1 presents the same change in IMR against the analogous employment ratio for low-export-growth industries:

$$\frac{EmpShare(DL)}{EmpShare(CL) + EmpShare(DL)} .$$

Figure 1 shows that initial specialization in dirty sectors does not predict change in infant mortality rate when we focus on low export growth industries. Given the importance of the concern regarding our Bartik strategy we also control for pre-existing trends and present placebo tests.

We also address the potential objection that official sources for data on pollution may misreport pollutant concentrations in order to hide imperfect compliance with environmental regulation from the public. In this regard we check the correlation of the official daily pollution levels with the levels reported by the American Embassy and Consulates in 5 Chinese cities. We show that the correlation is above 94 percent for most of the series even though the levels reported by the American Embassy are generally higher than the ones reported by Chinese official sources. Another issue that we delve on is the quantitative importance of trade policy shocks for the overall structure of production and level of pollution. We take a specific episode, the steel safeguard tariffs imposed by the US in 2002-2003 to show that for prefectures with heavy steel production pollution decreases relative to control prefectures in 2001 and increases back up in 2003.

We check the robustness of our results to alternative measures of export shocks that take into account shocks in neighboring and upwind prefectures, import shocks, input-output linkages that transmit foreign demand shocks to upstream industries and control for local energy production among other socio-economic determinants of mortality and pollution. We also analyze the results by gender and by age, finding a relatively homogeneous effect across different groups.

Given the battery of results that we present, what can we say about whether the export boom in China was good or not for the environment, and ultimately for the health of (in particular young) individuals? Given our strategy, we can only say whether a prefecture that was more exposed to export expansion than another benefitted or not, relative to that prefecture. If all prefectures in China benefitted from trade expansion by a common amount, then this is a factor that we obviously cannot capture. That said, our results *do* capture all benefits that should accrue differentially to different prefectures proportionally to their export exposure, and this is measured by our variable $ExportShock$. What we find is that, on average, $ExportShock$ tends to decrease infant mortality, but the effect is smaller and not as significant as the effect of $PollutionExportShock$. So, overall, Chinese prefectures that experienced larger exports shocks saw their infant mortality increase, although some prefectures experienced very large export booms in clean industries and we estimate those to have experienced a net beneficial effect on infant mortality.

1.1 Relation to the Literature

Our study contributes to two main strands of the literature, the one related to trade and pollution and the one studying the effect of pollution on mortality. The first generally addresses the question of whether international trade affects pollution through a variety of channels. Employing the language introduced by Grossman and Krueger (1995), Copeland and Taylor (2003) and Copeland and Taylor (2004), increased international trade can: i) lead to a more intense scale of production which increases pollution (scale effect) ; ii) induce specialization, which could reduce or increase pollution depending on whether a country specializes in clean or dirty industries (composition effect); and iii) generate an increase in income which would raise the demand for better environmental quality (technique effect). Antweiler et al. (2001) find that emissions across several world cities depend positively on the scale of economic activity and the capital abundance of the country and depend negatively on income. Their main finding in relation to the trade-environment link is that, as a country is more open to trade, on average emissions are lower. Their cautiously optimistic conclusion is that trade may be good for the environment, but they note that the effect of trade in different countries depend on their pattern of comparative advantage. Although their study employs a panel data set that allows them to control for time invariant country effect, the authors themselves admit that the issue of identification due to the presence of unobserved shocks is not fully solved in their paper. A different approach to identification is offered by Frankel and Rose (2005), although they limit their analysis to a cross-section of countries and employ a geography-based IV approach. They identify that, controlling for income, increased trade leads to lower emissions. Our contribution is to take a step further in the direction of identifying the causal effect of trade on environmental quality and health. Our within-country approach necessarily controls for several unobserved variables that are not accounted for by country-level panel studies, but we also adopt several techniques to deal with other potential sources of endogeneity. The cost of our approach, relative to country-level analysis, is that we necessarily ignore national-level general equilibrium effects and therefore we will not be able to say whether China overall saw its environmental quality improve or worsen because of trade expansion.

In a related literature, several recent contributions have focused on the firm-level link between exporting and emissions. In the cross-section Forslid et al. (2015) find that exporters tend to have lower emission intensities, while Cherniwchan (2013) finds lower emissions as firms are exposed to tariffs cuts in the output market. Interestingly, Barrows and Ollivier (2014) find that this effect is solely due to a change in the product mix: for the same product, exporters do not reduce emissions per unit, but they concentrate production on their core and cleaner products. Because our emission data are available only at the aggregate level, we cannot investigate potentially interesting effects of trade opening on the technique of production at the local level, but when we consider the total effect at the prefecture level, we should keep in mind that these mechanisms may also be at play.

We also relate to another strand of literature that studies the impact of pollution on mortality, in particular of infants. The reason why infant mortality is often chosen as a relevant outcome is not only that young children are particularly vulnerable members of society which per se may be of particular interest, but also because their health outcomes are more closely related to immediate environmental conditions, while adults' health may be the consequence of factors accumulated over the course of many years. These studies are conducted both in developed countries like Chay and Greenstone (2003a), Chay and Greenstone (2003b), Currie and Neidell (2005) and Currie et al. (2009), and in developing countries, like Greenstone and Hanna (2014), Arceo et al. (2016) and Tanaka (2015). It is important to consider the main differences between a study like ours and the one for example by Currie and Neidell (2005). Currie and Neidell's study is based on much richer data: individual birth records with a host of socio-economic characteristics of the mother and weekly measures for pollution. The high level of disaggregation of the data is their primary line of attack on the issue of unobserved heterogeneity potentially generating a spurious correlation between mortality and pollution. The disadvantages generated by access to more aggregate data in our paper are at least partially compensated by the advantage of an instrumental variable approach to correct for unobserved heterogeneity.

In terms of specific studies on trade and pollution in China, we are only aware of a few papers, but none with the same focus as ours. An earlier paper by Dean (2002) considers the link between openness and water pollution across Chinese provinces, but it essentially exploits national-level measures of openness and therefore estimates the relationship using pure time variation whereas our entire strategy relies on exploiting differential shocks within China. The most closely related paper to ours is by de Sousa et al. (2015) who exploit city-level variation in exports and find that increased processing trade in China leads to lower pollution. In the energy and environmental science literature, some studies like Lin et al. (2014) and Yan and Yang (2010) have addressed the global impact of China's trade on various pollutants, but they do not identify the effect on China itself and its air quality.

The rest of the paper proceeds as follows. Section 2 describes the various data sources, while section 2.6 probes the quality of specific variables, like air quality and mortality. Section 3 shows, through a simple event study, that even a single trade policy measure imposed by the US affected air quality in China's steel-manufacturing areas. Section 4 lays out a trade model with pollution as a byproduct of production and the model guides our empirical strategy. In section 5 we construct our export shock measures and present our identification strategy in two parts: i) we first show the reduced form effect of $PollutionExportShock$ and $ExportShock$ on mortality; ii) we then show that export shocks affect mortality through pollution. Section 6 discusses our main results and 7 reports a number of robustness checks. We conclude in section 8.

2 Data

2.1 Local Economies and Employment Data

The unit of analysis is a prefecture in China, which is an administrative division ranking between province and county. Prefectures are matched across census years according to the 2005 administration division of China, so that the data has a geographic panel dimension. There are 340 prefectures, with median land area of 13,152 km^2 and median population of 3.2 million in year 2000. The size of the prefecture makes it a relevant unit of analysis. Moreover, migration rate among prefectures is low, due to the household registration system. According to the 2000 Census, less than 4.5% of population aged between 16 and 59 changed the prefecture of residence during the past five years. This inter-prefecture migration rate increased slightly to 4.8% in 2005.[3] In contrast, the five-year migration rate across states is around 12.5% for US in 2000 (Kaplan and Schulhofer-Wohl, 2012) and the five-year migration rate across districts in India (which is a similar administrative division as prefecture in China) is around 13.5% in 2007 (Marden, 2015).

The information on industry employment structure by prefecture is from the 1% samples of the 1990 and 2000 China Population Censuses. The census data contain relevant information regarding the prefecture of residence and the industry of employment at 3-digit Chinese Standard Industrial Classification (CSIC) codes.[4]

2.2 Export and Tariff Data

From the UN Comtrade Database, we obtain data on China's export and import values at the 4-digit International Standard Industrial Classification (ISIC) Rev.3 codes for years 1992, 2000 and 2010.[5] Data on export tariffs faced by Chinese exporters by destination countries and 4-digit ISIC Rev.3 industries are from the TRAINS Database. We map the trade and tariff data to the 3-digit CSIC sectoral employment data from the population censuses, using the concordances of ISIC and CSIC.

[3] The figure is derived from a 20% subsample of 2005 China 1% Population Sampling Survey.

[4] 1990 Census employs CSIC 1984 version and 2000 Census employs the CSIC 1994 version. We reconcile the two versions and create a consistent 3-digit CSIC code. There are 148 industries in the manufacturing sector.

[5] 1992 is the first year when the export data is available for China at 4-digit ISIC level.

2.3 Pollution Data

2.3.1 Industry Pollution Intensity

We construct the pollution intensity for each 3-digit CSIC industry, using the data from the World Bank's Industrial Pollution Projection System (IPPS) and China's environment yearbooks published by Ministry of Environmental Protection (MEP). The IPPS is a list of emission intensities, i.e., emission per value output, of a wide variety of pollutants by 4-digit Standard Industrial Classification (SIC) codes. These data were assembled by the World Bank using the 1987 data from the US EPA emissions database and manufacturing census.[6] We aggregate the data to 3-digit CSIC level and consider the pollutants sulfur dioxide (SO_2), total suspended particles (TSP) and nitrogen dioxide (NO_2) in the analysis.

To address the concern that China's industry pollution intensities may be uniformly higher than those of the US, we use the MEP data on 2-digit sector pollution intensity to adjust the level. Specifically, the pollution intensity for each pollutant p, of a 3-digit CSIC industry k, is imputed following the steps: (i) using industry output as weight,[7] we aggregate the 3-digit IPPS data $\gamma_k^{p,IPPS}$ to 2-digit CSIC level, i.e., $\gamma_K^{p,IPPS}$ where K is a 2-digit CSIC sector; (ii) for each 3-digit industry, we calculate the ratio of its pollution intensity to the corresponding 2-digit sector pollution intensity, i.e., $r_k^{p,IPP} = \gamma_k^{p,IPPS}/\gamma_K^{p,IPPS}$; (iii) we impute pollution intensity for each 3-digit industry according to $\gamma_k^{p,MEP} = r_k^{p,IPP} \times \gamma_K^{p,MEP}$. Therefore, while the level of industry pollution intensity is aligned with the MEP data, the within sector heterogeneity retains the feature of the IPPS data. To account for the changing industry pollution intensity over time, we use the 1996 and 2006 data from MEP and construct measures for each decade t. The pollution intensity $\gamma_{kt}^{p,MEP}$ is employed to build the pollution export shock as is discussed in Section 5.

2.3.2 Data on Pollution Concentration

Information on annual daily average concentration of SO_2 is collected for the years 1992, 2000 and 2010. The data are obtained from China's environment yearbooks, which report the data on air pollution for 77, 100, and 300 cities/prefectures for years 1992, 2000 and 2010, respectively.[8] We supplement this main dataset with the information gathered manually from provincial/city statistical yearbooks, government reports and bulletins. Restricting to prefectures with at least two readings, an unbalanced panel data is complied which covers 203 prefectures.

[6] To our best knowledge, there is no analogous data at such disaggregated level for China.

[7] The data on output by industry is from Chinese Industrial Annual Survey.

[8] Only SO_2 concentration level data are continuously published in China's environmental yearbooks over the sample period. The concentration of TSP was reported in 1990 and 2000, however, it was replace by $PM10$ in 2010.

To address the concern that the pollution readings may be subject to manipulations by local governments, we employ satellite information on $PM2.5$ provided by NASA.[9] The NASA dataset contains information on the three-year running mean of $PM2.5$ concentration for a grid of 0.1 degree by 0.1 degree since 1998. Adjacent grid points are approximately 10 kilometers apart. For the purpose of our analysis, we employ the data of years 2000 and 2010 and construct the decadal change in $PM2.5$ concentration at prefecture level. Specifically, for each county-year observation, we calculate the average $PM2.5$ concentration using the data of the grid points that fall within the county. Then the county-level data is aggregated to the prefecture level, weighted by the county population.

2.3.3 Daily Data on Air Pollution in China

For the event study on steel safeguards, we use the daily data on air pollution index (API), an overall measure of ambient air quality. API data are obtained from MEP of China. The dataset records the API of major cities in China starting from June 5th, 2000. The number of cities covered increases from 42 in the early sample period to 84 by the end of our sample period. Over 2001 to 2005, the average API declined from 83 to 73.[10]

2.4 Mortality Data

Our empirical analysis mainly focuses on infants to circumvent the problem of unknown lifetime exposure to pollution and other unobserved factors that jeopardize health. Because of the low migration rates of pregnant women and infants, the location of the exposure is most likely be the location of residence. Moreover, the environmental hazards are more likely to take immediate effects on infants due to their vulnerability. Also, infant deaths present a large loss of life expectancy. From our data, the mortality rate in the first year of life is higher than that in the next thirty years combined.

The infant mortality rates (IMR) are constructed from the China Population Censuses for years 1982, 1990, 2000 and 2010. Each census recorded the number of births and deaths within a household during the last 12 months before the census was taken.[11] The total number of deaths

[9] We use the Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD), v1 (1998-2012) dataset from NASA's Socioeconomic Data and Applications Center (SEDAC). The data on PM2.5 are derived from Aerosol Optical Depth satellite retrievals, using the GEOS-Chem chemical transport model, which accounts for the time-varying local relationships between AOD and PM2.5.

[10] For the balanced panel of 42 cities, the average API declined from 86 to 73.

[11] According to the enumeration form instructions of the China population censuses, both birth and death are registered at the household level, where the newborn and the deceased belong to. Therefore, in principle, the census data accurately record the number of births and deaths within a geographic unit. To evaluate the potential measurement errors introduced by migration, let's consider the following scenarios. First, a mother gave birth in a village, then migrated to a city and lived in a factory dormitory. Her newborn was left behind and taken care by

at age 0 is collected for every county, and then aggregated the to the prefecture level. The total number of births by prefecture is derived in the same way. The infant mortality rate is defined as the number of deaths at age 0 per 1000 of live births. In addition to IMR, we assemble the data on mortality rate of young children aged 1-4 at prefecture level for years 1990, 2000 and 2010.[12]

We supplement the census mortality data with the vital statistics obtained from 1992 and 2000 China's Disease Surveillance Points (DSP) system. The DSP collects birth and death registration for 145 nationally representative sites, covering approximately 1% of the national population. The data recorded whether or not an infant died within a calendar year, and if he or she did, the cause of death, using the International Classification of Disease 9th Revision (ICD-9) codes. We match each surveillance site to the prefecture where it is located,[13] and group the causes of death into several categories: cardio-respiratory illness, infant-specific causes (including congenital anomalies and perinatal conditions), digestive illness, infectious illness, malnutrition, and external causes (including accidents and violence).[14]

2.5 Other Demographic, Socioeconomic and Wind Data

We collected other demographic and socioeconomic variables at prefecture level, including GDP per capita, provision of medical care, sex ratio of the newborns, share of population with different educational attainments, share of agricultural employment, and population density from various provincial statistical yearbooks and population censuses. The distance to the nearest port for each prefecture is calculated using the information from World Port Index. In addition, for the period of 2000 to 2009, we obtain the prefecture-level information on output by 3-digit CSIC industry, fossil fuel energy production, and production shares of state-owned enterprises (SOE) and foreign firms from Chinese Industrial Annual Survey.[15] The data on wind direction for each prefecture is from NOAA Integrated Surface Global Hourly Data. Appendix A provides more detailed discussions

grandparents in the rural area. If her baby unfortunately died, the death will be registered in the grandparents' household, but not in the factory dormitory. In this case, infant mortality is accurately measured in both city and rural areas. Second, a migrant female worker gave birth in a city, and sent her baby to rural village. Her baby unfortunately died because of earlier exposure to air pollution in the city. In this case, the birth is counted in the city and the death is counted in the rural area. As a result, our estimate understate the true effect of pollution on IMR. Nevertheless, we consider that the second scenario is less likely in the Chinese context due to restrictions on migrant workers' access to public health service in cities.

[12] The mortality rate of young children aged 1-4 is defined as $\frac{Deaths_{1-4}}{Deaths_{1-4}+Poplution_{1-4}} \times 1000$.

[13] The surveillance sites are primarily at the county level.

[14] Cardio-respiratory illness includes all causes under ICD-9 codes 25-28, 31 and 32; infant specific illness includes the causes under codes 44 and 45; digestive illness includes causes under codes 33 and 44; infectious illness includes causes under 1-7; external reason include all causes under codes from 47-53 and E47-E56; and malnutrition includes causes under code 19. In 1992, the shares of infant deaths due to cardio-respiratory, infant-specific, digestive, infectious, external causes and malnutrition are 28.5%, 46.6%, 1.9%, 6.2%, 5.8% and 0.3%, respectively.

[15] The data set includes all the state owned firms and non-state firms with revenue above 5 million RMB (approximately 800 thousand US dollar).

on data sources and the construction of variables.

2.6 Quality Assessment of the Chinese Data Pollution and Mortality

In this section we address the concern that official reports from the Chinese government may not be fully reliable due to the desire to under-report pollution and mortality. With regards to pollution, in order to assess the severity of underreporting, we have to consider the incentives of officials at various levels of government in the period considered between 1990 and 2010. As reported by Chen et al. (2013), although the data on pollution were collected starting in the late 1970's, they were not published until 1998, so it is unlikely that fear of public uproar would be a concern for local officials. More importantly, in a number of studies Jia (2012) and Jia et al. (2015) report that officials most likely perceived local economic growth to be the criterion for promotion, rather than environmental quality. In fact Jia (2012) shows how increased pollution is a byproduct of the quest for higher economic growth by aspiring politicians. Moreover, our identification strategy compares the changes in pollutant concentration of prefectures with different initial industrial specialization. Therefore, our results will be contaminated only if the pollution data were systematically manipulated for prefectures with different initial industry composition. Despite all these considerations, one might still be concerned that our pollution measures are very noisy, so in the Appendix B we corroborate our data by showing that the official Chinese daily data on air quality has a correlation of at least 0.94 with the US Consulate or Embassy data, depending on the city.

In Appendix B we also show the results of an exercise aimed at detecting over- or under-reporting of infant mortality. In essence we compare the number of 10-year-old children in a prefecture in a given census year with the expected number of 10-year-old children based on the reported mortality and birth figures from the last population census (a decade earlier). We find a correlation of 0.98 between these two measures, which of course cannot perfectly coincide due to unaccounted-for migration.

3 Preliminary Event Study: the 2002 US Steel Safeguard Measures

Before building comprehensive measures of export shocks that cover the entire manufacturing sector, it is worthwhile to pause and consider whether export shocks generated by foreign demand are realistically large enough to affect local pollution measures. First, we should consider that exports are a large share of China's output. The average annual share of exports to GDP was 27% in the 1990's and 17% in the 2000's, so it is plausible that changes in foreign demand may substantially alter the pattern of production. Nevertheless, we investigate the issue through a specific event, i.e., the US imposition of safeguard tariffs on imports of steel product in March 2002 (and its removal in December 2003). On 28th June 2000, the US Trade Representative (USTR) requested the US International Trade Commission (ITC) commence a Section 201 investigation on whether steel imports of 612 different 10-digit HS product categories were causing injury to the domestic industry. The USITC investigation covered imports with a combined value of some $17 billion, more than half of total US imports of steel in 2001. On 22nd October 2001, the ITC announced its findings that 85% of the imported products subject to investigation had caused injury to the domestic steel industry, and in December 2001, the ITC announced its non-binding recommendation for safeguard tariffs and quotas. On 20th March 2000, President George W. Bush announced the application of safeguard tariffs and quotas on 272 different 10-digit HS product categories, which were significantly higher than that recommended by the USITC Commissioners[16] (Read, 2005; Bown, 2013). To retaliate against the US safeguard measures and mitigate the associated diversionary effects, the EU imposed temporary safeguard measures on its steel imports on 28 March 2002 and introduced final safeguard measures on 29 September 2002. According to the World Bank Temporary Trade Barriers Database, 225 different 10-digit HS product categories were subject to investigation, among which 53 were imposed by safeguard tariffs. China also initiated its own safeguard measures on 20th May 2002. On 4th December 2003, the US lifted all the safeguard tariffs and the EU and China removed their measures in the same month. Figure A.1 summarizes the timeline of the 2002 steel safeguards, with different colors indicating different stages which include investigation, provisional measures, final measures and scheduled liberalization.

As documented by Read (2005), it is generally understood that tariffs were imposed for reasons related to domestic political consideration and are unlikely to be related in their timing and magnitude to events happening in China. This event is useful for our study because it pertains an industry whose activity is highly polluting, like steel. According to the World Bank IPPS data on emission intensity employed by Levinson (2009), SIC industry 331 and 332 are in the top 10% industries by emissions of both SO_2 and particulate matter.[17] We exploit this event to detect whether a temporary protection measure in the US that raised import tariffs on several steel products affected air quality relatively more in prefectures that produce more steel. We are interested in the differential level of air quality in steel-producing regions relative to other regions

[16] 185 products received a 30% tariff, 60 received a 15% tariff, 15 received a 13% tariff and 7 received a 8% tariff in the first year. In 19th March 2003, the tariffs for each of the categories stepped down to 24%, 12%, 10% and 7%.

[17] Steel mills closures have been used in Pope III (1989), Ransom et al. (1995) and Pope III (1996) to detect the effect of particulate matter concentration on health outcomes.

before and after the steel safeguards. The specification we employ is the following:

$$API_{it} = \beta ShareSteel_i \times NoSG_t + \alpha_i + \phi_{ry} + \gamma_{rm} + \varepsilon_{it} \ ,$$

where API_{it} is the Air Pollution Index in prefecture i on day t, $ShareSteel_i$ is equal to the share of employment in steel sectors (in percentage)[18] and the dummy $NoSG$ is equal to 1 in the period before the investigation and after the revocation of the safeguards. (The time window of the steel safeguard corresponds to the days between 28/06/2001 and 04/12/2003.)[19] Finally, α_i is a prefecture dummy, while ϕ_{ry} and γ_{rm} are, respectively, region-year and region-month dummies.[20] Standard errors are clustered at the prefecture level. The different specifications in Table 1 employ different samples of months and interact the variable $ShareSteel_i$ with different policy time dummies: $AfterSG_t$ is equal to 1 in the period after the termination of the safeguard policy and $BeforeSG_t$ is defined similarly. Our findings indicate that before and after the period during which the policy was in place the API was higher in steel-producing cities. The effect is not very large, but strongly significant. Column 8 of table 1 indicates that the API (which averages 78.7) decreased by $2.53 \times 0.8 = 2$ points during the policy months in prefectures that had the average share of steel employment relative to a prefecture that had no employment in steel.

4 Theoretical framework

In this section we present a simple Ricardian model of trade and pollutant emissions that rationalizes our empirical specification. The set-up is a standard Eaton-Kortum style model (see Eaton and Kortum, 2002) with multiple sectors as in Costinot et al. (2012) and fixed emission intensities by sector. Consider a world economy that features multiple prefectures in China, indexed by $i = 1, ..., C$, and multiple regions in the rest of the world (henceforth ROW), indexed by $i = C+1, ..., N$, and K sectors, $k = 1, ..., K$. Each sector features multiple varieties, indexed by ω. Preferences are described by a Cobb-Douglas upper-tier utility function (with consumption shares β_k) and a lower-tier CES utility function. Each sector is characterized by an emission intensity γ_k which is equal to the ratio of emissions divided by the value of output and is assumed to be

[18] Employments under the code 32 and 34 of the CSIC 1994 classification, which pertain to steel and steel-related products. Employment data is from the 2000 population census.

[19] We find that exports from China to the US start declining during the investigation phase. This "investigation effect", originally analyzed theoretically and empirically by Staiger and Wolak (1994), was also detected in the same context by Bown (2013).

[20] There are 8 regions: Northeast (Heilongjiang, Jilin and Liaoning), North Municipalities (Beijing and Tianjin), North Coast (Hebei and Shandong), Central Coast (Shanghai, Jiangsu and Zhejiang), South Coast (Guangdong, Fujian and Hainan), Central(Henan, Shanxi, Anhui, Jiangxi, Hubei and Hunan), Southwest (Guangxi, Chongqing, Sichuan, Guizhou, Yunnan and Tibet) and Northwest (Inner Mongolia, Shanxi, Gansu, Qinghai, Ningxia and Xinjiang).

fixed.[21] There is only one factor of production, labor, and the production function for variety ω of good k in region i takes the following linear form:

$$Q_{ik}(\omega) = z_{ik}(\omega)\, L_{ik}(\omega) \ ,$$

where $L_{ik}(\omega)$ denotes the labor employed in region i to produce variety ω of good k. The associated labor productivity is represented by $z_{ik}(\omega)$, and it is drawn from a Fréchet distribution $F_{ik}(\cdot)$, that is:

$$F_{ik}(z) = exp\left[-(z/z_{ik})^{-\theta}\right] \ \ for\ all\ z{\geq}\ 0 \ .$$

We assume that there is a large non-manufacturing sector that also employs only labor and that determines the wage w_i.[22] Trade between regions is costly and τ_{ijk} denotes the iceberg cost of shipping good k from region i to j. We maintain the standard assumption that $\tau_{ijk} \geq 1$ if $j \neq i$ and $\tau_{iik} = 1$. Markets are assumed to be perfectly competitive, and each region imports from the lowest cost supplier. The producer price for each variety ω is given by $p_{ik}(\omega) = w_i/z_{ik}(\omega)$. The value output of sector k in region i is $Y_{ik} = \sum_{\omega} p_{ik}(\omega)\, Q_{ik}(\omega) = w_i L_{ik}$.

Following Eaton and Kortum (2002), the value of exports of good k from prefecture i in China to region j in the ROW is determined by:

$$X_{ijk} = \lambda_{ijk}\beta_k Y_j \ ,$$

where λ_{ijk} denotes the share of expenditure on good k in region j that is allocated to the products from prefecture i. This share λ_{ijk} depends on production and transportation costs according to the following expression:

$$\lambda_{ijk} = \frac{(w_i \tau_{ijk}/z_{ik})^{-\theta}}{\sum_{i'=1}^{N}(w_{i'}\tau_{i'jk}/z_{i'k})^{-\theta}} \ .$$

We can calculate the size of each sector in each region, as approximated by the employment in the sector L_{ik}, as follows:

[21] We assume fixed emission intensities not only because of simplicity, but mostly because we do not have access to micro-data at the prefecture level that would allow us to test predictions regarding the effect of trade on production techniques. The assumption of fixed emission intensities is also made in Shapiro (2015).

[22] This is not an innocuous simplification, but it can be justified by the broad structural change happening in China during this period. Rather than a real agricultural sector, this large outside sector should be rather seen as a representation of the large pool of subsistence rural workers that would later migrate to urban areas during the 1990's and 2000's. In the rest of the derivation we omit the impact of this rural agricultural sector on emissions and this assumption can be interpreted in two ways. The first is that this type of agriculture did not contribute significantly to pollution. The second interpretation is that the production function in that sector exhibited very low marginal product of labor due to the high ratio of population to land and therefore departure of a large share of the workforce had little effect on output.

$$w_i L_{ik} = \sum_{j=1}^{N} X_{ijk} = \sum_{j=1}^{N} \lambda_{ijk} \beta_k Y_j \ . \tag{1}$$

Finally, total emissions are simply given by $P_i = \sum_k \gamma_k Y_{ik}$.

4.1 Changes in Transport Costs: Deriving Export Demand Shocks

The exogenous shocks in this model come from changes in iceberg costs $\{\hat{\tau}_{iRk}\}$, where i is a prefecture in China and we denote by R the set of all other regions in the rest of the world. In the empirical section we will interpret these changes in transport costs as coming from a decline in tariffs faced by Chinese exporters. Hats over variables denotes log changes ($\hat{x} \equiv d \ln x$). We assume that all regions in China face the same export cost, i.e. the same tariff, and that this common tariff is therefore declining by the same amount for all prefectures $\hat{\tau}_{iRk} = \hat{\tau}_{i'Rk} = \hat{\tau}_{Rk}$. Moreover we assume that internal trade costs remain unchanged, that is $\hat{\tau}_{ii'k} = 0$. Total differentiation of equation (1) gives

$$dY_{ik} = dX_{iRk} = \frac{X_{iRk}}{X_{CRk}} dX_{CRk} \ , \tag{2}$$

where dX_{CRk} is the change in exports of good k from China to the ROW due to a change in transport costs.[23] Then, the total change in emissions is given by:

$$dP_i = \sum_k \gamma_k \frac{X_{iRk}}{X_{CRk}} dX_{CRk} \ . \tag{4}$$

In our empirical work, our available measure of environmental quality is the change in emission concentration in region i, C_i, where air pollutant levels are measured per cubic meter. Since the amount of air is roughly proportional to the underlying area of land, our measure of pollutant concentration C_i will be proportional to $\frac{P_i}{T_i}$, where T_i denotes the land area of region i. We can therefore rewrite equation (4) as:

[23] More specifically, equation (2) is derived as follows:

$$d\lambda_{iRk} = -\frac{\theta \lambda_{iRk}}{\tau_{Rk}} d\tau_{Rk} + \frac{\theta \lambda_{iRk} \sum_{i' \in C} \lambda_{i'Rk}}{\tau_{Rk}} d\tau_{Rk} = -\theta(1 - \lambda_{CRk}) \lambda_{iRk} \frac{d\tau_{Rk}}{\tau_{Rk}} \ , \tag{3}$$

where C is the set of regions in China. In this derivation it is key to impose a contemporaneous change in tariffs to the rest of the world for all regions in China. Analogously, the change in China's share in the rest of the world imports is $d\lambda_{CRk} = -\theta(1 - \lambda_{CRk}) \lambda_{CRk} \frac{d\tau_{Rk}}{\tau_{Rk}}$ and we can combine $d\lambda_{CRk}$ with equation (3) to find:

$$d\lambda_{iRk} = \frac{X_{iRk}}{X_{CRk}} d\lambda_{CRk} \ .$$

Simple manipulation yields equation (2).

$$dC_i \propto \sum_k \gamma_k \frac{X_{iRk}}{X_{CRk}} \frac{dX_{CRk}}{T_i} \ . \tag{5}$$

Equation (5) sheds light on how external demand shocks at the national level lead to differential environmental impact across prefectures in China. In particular, we show that a prefecture receives a larger pollution export shock if it specializes in dirty industries that experienced larger declines in trade costs. The weighted average structure of export pollution shocks resembles the empirical approach in the literature on the local effects of trade (Autor et al., 2013; Topalova, 2010; Kovak, 2013). However, it specifically reflects the pollution content embodied in the trade-cost induced export growth, rather than overall export expansion.

5 Empirical Specification

In this section we lay out our empirical methodology and explain our identification strategy. We start by describing how we construct our key explanatory variables, $PollutionExportShock$ (expansion in exports measured in units of pollutant) and $ExportShock$ (expansion in exports measured in dollars). We then introduce our instrument for export expansion, which consists of tariffs faced by Chinese exporters in different sectors. Finally we introduce our two outcome variables: mortality and pollution concentration. We illustrate schematically the causality links that we will explore in Figure 3. "Export" tariffs, i.e., tariffs that Chinese exporters face, affect the extent of export expansion, measured by $PollutionExportShock$ and $ExportShock$, which ultimately affect mortality, potentially through pollution concentration. We delve into the mechanism further below.

5.1 Pollution Export Shocks and Export Shocks

In this section we build the empirical measures that capture exports shocks and that will assess the relationship between export expansion and pollution changes in individual prefectures in China. We expect increased exports to affect pollution through two potential channels, which we capture with two types of export shocks.

i) $PollutionExportShock^p_{it}$ - Increased foreign demand induces an increase in total manufacturing production, but the environmental consequences depend on whether the export expansion is concentrated in dirty or clean industries.

ii) $ExportShock_{it}$ - Increased exports may also increase local wages and profits, which, through an income effect, may increase the demand for clean air, thus reducing pollution. Although this income effect is ignored by our model in section 4, we believe it should be accounted for in the empirical analysis.

We focus on channel i) first. Because we will analyze the outcome in terms of different pollutants, we denote by γ^p_{kt} the pollution intensity for pollutant p, i.e., the total amount of emissions in sector k, P^p_{kt}, divided by the value of output Y_{kt} so that $\gamma^p_{kt} = \frac{P^p_{kt}}{Y_{kt}}$. If we had access to the value of exports by individual prefecture i then we could find the impact of export expansion on local pollution changes using the following equation:

$$\Delta C^p_{it} = \sum_k \gamma^p_{kt} \frac{\Delta X_{iRkt}}{T_i} \ , \tag{6}$$

where ΔC^p_{it} measures the change in concentration of pollutant p in prefecture i between year $t-1$ and year t, ΔX_{iRkt} is the analogous change in export value from prefecture i in sector k and T_i denotes the land area of region i. Prefecture level exports could in principle be calculated from firm-level customs data, but such data are not available for the earlier time period in our sample. Moreover, we argue that, even if such data were available, they may be more likely to be affected by local productivity shocks, which we are attempting to isolate from in our analysis. Therefore we exploit the model prediction in equation (5) to construct ΔX_{iRkt}. We use employment share $\frac{L_{ik,t-1}}{L_{Ck,t-1}}$, where $L_{ik,t-1}$ and $L_{Ck,t-1}$ are respectively prefecture i's employment and China's total employment in industry k at the beginning of the period, to proxy for a prefecture's export share in industry k, $\frac{X_{iRk,t-1}}{X_{CRk,t-1}}$, again because export data at the prefecture level are not available for the earlier time period (1990) of our sample.[24] Thus far, we have posited that local pollution concentration is proportional to emissions normalized by land area T_i.[25] Empirically, however, this approach faces the problem that some prefectures include vast desert areas where pollutant presence is very low, and population is almost absent. Ideally we would like to know the size of the populated area, but in the absence of such information we use the size of the population (as proxied

[24] We adopt different approaches to investigate the potential bias introduced by this approximation. First, in section 6.2.1, we construct the theoretically consistent measures using the export share data in 2000, and find regression results aligned with the baseline findings. Second, in the Appendix C, we regress a prefecture's export share $\frac{X_{iRk}}{X_{CRk}}$ on its employment share $\frac{L_{ik}}{L_{Ck}}$, using the data in 2000. The estimated coefficient is 0.965, insignificantly different from one. Under the condition that the discrepancy between export and employment shares is uncorrelated with a prefecture's export composition, our estimates provide lower bounds for the effects of export shocks on pollution and IMR.

[25] It is important to understand why we stress this normalization. The outcome variable is change in pollutant concentration and because land area is constant over time, it may be tempting to conclude that such normalization does not matter. Stripping the specification of subscripts, the bias introduced by disregarding this normalization is given by comparing univariate the OLS coefficients: $\beta = \frac{Cov(\Delta C_i, \Delta P_i)}{Var(\Delta P_i)}$ and $\beta' = \frac{Cov(\Delta C_i, \frac{\Delta P}{T_i})}{Var(\frac{\Delta P_i}{T_i})}$. If the land area was constant across prefectures, i.e. $T_i = T \ \forall i$, the OLS coefficient β would still be biased relative to the true coefficient β': $\beta = \frac{\beta'}{T}$. In general it is hard to assess the bias introduced by a lack of normalization, but there is no reason to expect that this bias would be null.

by the size of the workforce in i) to replace land area, with the caveat that such normalization does not affect our results. Therefore $PollutionExportShock^p_{it}$, our empirical measure of export-induced pollution in prefecture i, is constructed as follows:

$$PollutionExportShock^p_{it} = \sum_k \gamma^p_{kt} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{CRkt}}{L_{Ck,t-1}} \, , \tag{7}$$

and it measures the pounds of pollutant p associated with export expansion measured on a per worker basis. The normalization by local employment that we discussed above serves the additional purpose of making our $PollutionExportShock^p_{it}$ measure easily comparable to our second measure of export shock, which we define simply as $ExportShock_{it}$. This second measure, which addresses channel ii), i.e. the impact of export-induced income growth on environmental outcomes, is constructed as follows:

$$ExportShock_{it} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{CRkt}}{L_{Ck,t-1}} \, , \tag{8}$$

and it measures the dollar value of export expansion in prefecture i, also on a per worker basis. Importantly the two shocks measure different dimensions of export expansion. While $ExportShock_{it}$ measures the total value of all goods being exported, $PollutionExportShock^p_{it}$ gives different weights to different sectors according to their emission intensity. So, while $PollutionExportShock^p_{it}$ measures the scale effect (taking into account different initial industrial composition of different prefectures), $ExportShock_{it}$ gives the same weight to each dollar of export expansion.

The variable $ExportShock_{it}$ is the equivalent of the change in value of imports per worker at the commuting zone level in Autor et al. (2013). The variation across prefectures of our two measures, $PollutionExportShock^p_{it}$ and $ExportShock_{it}$ stems from initial differences in local industry employment structure, a feature common to the Bartik approach (see Bartik, 1991). We analyze more in detail the properties of these shocks in the context of our discussion of identification, which we cover in the section 5.2.1.

5.2 Specification 1: Total Effect of Export Shocks on Mortality

In this section we describe our approach to identifying the causal impact of a decline in transport costs on pollution and mortality across prefectures in China. Our first specification is the following:

$$\Delta IMR_{it} = \alpha_1 + \alpha_2 PollutionExportShock^p_{it} + \alpha_3 ExportShock_{it} + \varepsilon_{it} \tag{9}$$

where ΔIMR_{it} is the change in infant mortality rate in prefecture i between year $t-1$ and t, while ε_{it} is an error term that captures other unobserved factors and is assumed to be orthogonal the two export shocks . In the following section we address issues related to endogeneity.

5.2.1 Identification Strategy

Our basic specification (9) relates infant mortality to our two export shocks, ignoring other potential socio-economic determinants that could be important drivers of mortality. We therefore include several control variables that capture education, provision of health services, ethnic composition and income. Even after the inclusion of such variables, we are still concerned that the error term ε_{it} may be affected demand and supply factors that are correlated with our export shock measures.

Bartik Approach

The first type of shocks we may be concerned about is local productivity or factor supply changes that may affect local output and exports and affect pollution concentration at the same time. Both measures $PollutionExportShock_{it}^{p}$ and $ExportShock_{it}$, through a Bartik approach, tackle this issue by not employing export expansion at the local level, but rather using a weighted average of national export expansion. As usual, this approach relies on the assumption that other time-varying, region-specific determinants of the outcome variable are uncorrelated with:

(a) region's initial industry composition, and

(b) industry shocks at the national level.

We will address issue (a) in three ways. The first is to control for pre-existing trends in infant mortality, so that we can account for the possibility that a region initially specialized in polluting industries may be on a different trajectory in terms of overall health outcomes. The second way we address issue (a) is to check that we cannot predict current infant mortality changes using future export shocks, thereby again ensuring that the two are not driven by a common unobserved factor. Our third approach to dealing with (a) is to control for the following variable, $PollEmployment_{it}^{p}$, which measures the level of pollution implied by the initial employment structure in prefecture i:

$$PollEmployment_{it}^{p} = \sum_{k} \gamma_{kt}^{p} \frac{L_{ik,t-1}}{L_{i,t-1}} \ . \tag{10}$$

Essentially we are concerned that regions initially specialized in dirty industries may just have initially more lax regulation and therefore be prone to relax such regulations even more. We may then mistake such effect as the consequence of export expansion. Controlling for $PollEmployment_{it}^{p}$ makes sure that we are comparing two prefectures with the same initial average level of specialization in dirty industries, which likely summarizes their attitude towards regulation, among other factors. Consider two prefectures specializing, respectively, in steel and cement and assume the two sectors have very similar pollution intensities. As a result, the two prefectures have similar value of $PollEmployment^p$, indicating they have similar initial pollution level. Nevertheless, they may experience different $PollutionExportShock^p$, if for example, steel receives a larger external demand shock.[26]

Export Tariffs and Export Shocks

One of the main concerns regarding the Bartik approach is that an industry clusters in a specific region and the region also highly specializes in it. In this case, requirement (b) will be violated because the national shock will essentially coincide with the local shock. And this is when the Bartik "apportionment" will fail to generate an exogenous local shock starting from national shocks. In this case we need to introduce variation that can isolate national export changes due to changes purely in foreign demand. Otherwise both $PollutionExportShock_{it}^p$ and $ExportShock_{it}$ may capture other types of local (in this case also national) supply shocks. We choose to employ variation in average tariff rates faced by China when exporting to the rest of the world, which we denote by $ExportTariff$. More specifically $ExportTariff_{kt}$ in sector k and time t is defined as a weighted average of the tariff τ_{kjt} imposed by country j, where the weights depend on time $t-1$ Chinese exports to country j, $X_{Cjk,t-1}$:

$$ExportTariff_{kt} = \sum_j \frac{X_{Cjk,t-1}}{X_{CRk,t-1}} \tau_{Cjkt} \; .$$

We believe changes in these tariffs to be mainly determined by political considerations in other countries and therefore to be exogenous to China's internal shocks. Nevertheless we need to check that changes in $ExportTariff$ are indeed uncorrelated with various shocks within China. In particular we verified that changes in $ExportTariff_{kt}$ are uncorrelated with: (i) changes in domestic demand across different sectors; (ii) changes in value added per worker (as a proxy for productivity growth) across sectors; (iii) emission intensities (i.e., cleaner industries are not being liberalized at a different pace from dirty ones).

We posit that the growth in total exports can be explained by a decrease in the level of tariffs faced by exporters, so we adopt the following specification:

$$\ln X_{CRkt} = \eta_k + \phi_t + \theta \ln(1 + ExportTariff_{kt}) + \varepsilon_{kt} \; , \tag{11}$$

[26] Notice that this is an average implied pollution level and it does not control for the entire composition of employment. If we were to control for the the entire vector of employment shares there would be of course no variation in the variables of interest $PollutionExportShock_{it}^p$ and $ExportShock_{it}$.

where η_k and ϕ_t are sector and time fixed effects. We report the results of this regression in Figure 4. The estimated coefficient implies that a 1% increase in the tariff faced by exporters decreases exports by 7.8%. Our estimate is within the range of gravity equation estimates of the effect of bilateral trade frictions as in Head and Mayer (2014), although on the upper side of such range. We obtain the fitted value of the logarithm of exports in equation (11), then take the exponential of such predicted value to obtain $\widehat{X}_{CRkt}$:

$$\widehat{X}_{CRkt} = exp(\hat{\eta}_k + \hat{\phi}_t + \widehat{\theta}\ln(1 + ExportTariff_{kt})) \ . \tag{12}$$

We employ predicted exports from (12) in changes, i.e., $\Delta\widehat{X}_{CRkt}$, to construct instruments for our export shocks of interest. Note that $\Delta\widehat{X}_{CRkt}$ is the empirical counterpart of dX_{CRk} as discussed in section 4.

We estimate equation (9) using instrumental variables that are constructed using predicted exports derived in equation (12). The two instrumental variables $Pollution\widehat{ExportShock}^p_{it}$ and $\widehat{ExportShock}_{it}$ are constructed as follows:

$$Pollution\widehat{ExportShock}^p_{it} = \sum_k \gamma^p_{kt} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta\widehat{X}_{CRkt}}{L_{Ck,t-1}} \ ,$$

$$\widehat{ExportShock}_{it} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta\widehat{X}_{CRkt}}{L_{Ck,t-1}} \ .$$

Importantly, this IV approach also addresses another problem that may bias our estimates, i.e. omitted variables. Imagine for example that export expansion and domestic demand were positively correlated. Since we do not have data on changes in domestic demand for the earlier period, our estimates of α_2 may be upward biased because it would contain both effects of export expansion and domestic demand. Because, as we said earlier, $ExportTariff$ is uncorrelated with domestic demand changes, we have a valid instrument to tackle this problem of omitted variable bias.

5.3 Specification 2: Pollution Concentration Channel

Our second specification attempts to identify the specific channels through which export shocks affect mortality. In particular we posit that $PollutionExportShock^p_{it}$ affects mortality only through its effect on pollution concentration while $ExportShock_{it}$ may affect mortality through its potential negative effect on pollution or through its general impact on income, which may increase demand for healthcare and in general affect living conditions of children. These considerations are represented in the diagram of Figure 3 and are reflected in our choice of specification, which is composed of two equations. The first is the mortality equation, which is similar to (9):

$$\Delta IMR_{it} = \delta_1 + \delta_2 \Delta PollConc^p_{it} + \delta_3 ExportShock_{it} + \nu_{it} \ , \tag{13}$$

where $\Delta PollConc^p_{it}$ is change in pollutant p concentration in prefecture i between year $t-1$ and year t. We again use an IV approach with instrumental variables $Pollution\widehat{ExportShock}^p_{it}$ and $Ex\widehat{port}Shock_{it}$ to disentangle the effect on mortality of increases in pollution caused by export expansion and income effects of export booms. Let us reiterate that the exclusion restriction here is that $PollutionExportShock^p_{it}$ does not independently affect mortality once pollution concentration is accounted for.

The second equation is the pollution concentration equation and it relates export shocks to $\Delta PollConc^p_{it}$:

$$\Delta PollConc^p_{it} = \rho_1 + \rho_2 PollutionExportShock^p_{it} + \rho_3 ExportShock_{it} + \mu_{it} \tag{14}$$

with the same instruments $Pollution\widehat{ExportShock}^p_{it}$ and $Ex\widehat{port}Shock_{it}$ employed to identify the causal effects of different export shocks on pollution concentration in a given prefecture.

6 Results

6.1 Summary Statistics

Before delving into the results we briefly describe the data summarized in Table 2. We focus on the two outcome variables of interest, infant mortality rate (IMR) and pollution concentration, and on the two shocks of interest, $PollutionExportShock^p_{it}$ and $ExportShock_{it}$. In Panel A we see that IMR has declined dramatically over the period 1982-2010 from an average of 36 deaths per thousand live births to just above 5 per thousand. Moreover, there is substantial heterogeneity in infant mortality both in levels and in changes over time. More specifically the 1982 IMR was 14 in the prefecture at the 10th percentile and 67 at the 90th percentile. In 2010 a similar disparity persists: at 10th percentile IMR is 1.4, while at the 90th it is almost 11, so we may conclude that in relative terms heterogeneity in infant mortality across provinces has increased. This is a pattern we can detect by looking at the percentiles of decade changes in IMR. Between 1990 and 2000 for example, although on average all prefecture saw a decline in IMR, the prefectures at the 90th percentile saw an increase by 9 per thousand. We seek to explain part of this pattern through export shocks that have differentially hit different prefectures.

Panel B shows that different Chinese prefectures are exposed to very different sulfur dioxide and particulate matter concentrations. While the average prefecture in 2000 featured a concentration of $SO2$ about 43 micrograms per cubic meter, this measure went from 12 μg/m^3 at the 10th percentile to 92 μg/m^3 at the 90th percentile. To put these numbers into perspective, 20 μg/m^3 is the 24-hour average recommended by the World Health Organization,[27] which implies that 75% of Chinese cities did not comply with the recommended threshold in 2000. The data on changes in SO_2 concentration over time show even more heterogeneity. Although the average prefecture saw a decline of 5 μg/m^3, the standard deviation of the change was 33 and more than half the cities saw a deterioration in sulfur dioxide concentration during the 2000s.

Panel C reports the variable $PollutionExportShock^p_{it}$ as change in pounds of pollutant embodied in exports per worker in a given prefecture. Although it is not easy to gauge the magnitude of this shock, it is easy to verify that it varied substantially, since for all pollutants, SO_2, TSP and NO_2 the standard deviation of the shock is most of the time higher than the mean. The two maps in Figure 5 show that the variation was not clustered in certain provinces, and that even within provinces different prefectures experienced different levels of $PollutionExportShock_{it}$.

Panel D reports the variable $ExportShock_{it}$ as change in exports in 1000 dollars per worker. Notice first that the export in the 2000s was one order of magnitude larger than the shock in the 1990's. During the 1990's the average prefecture saw an increase in exports per worker of 151 dollars, while in the 2000s that figure was 1,440 dollars. In both periods the standard deviation is larger than the mean, with substantial heterogeneity displayed by export shocks (in the 2000's the 10th percentile prefecture saw an increase of only 220 dollars, while the one at the 90th percentile experienced a surge of 3,100 dollars per person).

6.2 Results for Specification 1: Total Effect of Export Shocks on Mortality

In this section we report the results of estimating the effect of our two shocks of interest $PollutionExportShock_{it}$ and $ExportShock_{it}$ on infant mortality as shown in equation (9). The results appear in Table 3. The three panels differ by the pollutant employed to construct the $PollutionExportShock_{it}$ variable. Panels A, B and C report, respectively, the effects of the export content of sulfur dioxide, total suspended particles and nitrogen dioxide. All columns present instrumental variables regressions as detailed in section 5.2. In column (1) we find a positive and significant (at the 1% level) effect of a pollution export shock on infant mortality. Columns (1) through (7) employ different controls and fixed effects. In particular column (1) controls for region×year dummies to account for omitted factors that could be contemporaneously evolving in different regions and decades in China and that could be correlated with our export shock

[27] The data are obtained from "Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide" published by World Health Organization.

variables. Column (2) controls for the initial value of the following variables: log GDP per capita, overall mortality rate, agriculture employment share and population density and for contemporaneous changes in the following variables: log GDP per capita, share of boys, share of population with middle school education, share of population with high school education or above, number of hospital beds per capita, agricultural employment share, and distance to the nearest port. We also add a 2nd degree polynomial in the lag change in IMR, which flexibly control for the prefecture-specific pre-determined trends in IMR. The regression result is unaffected, a fact which alleviates the concern that our estimates are confounded by the different secular trends across prefectures, which could be associated with the initial industrial composition. Columns (3) and (4) report the impact of $ExportShock_{it}$ on infant mortality under the same specifications as in columns (1) and (2). The effect of export expansion in dollar terms is positive (i.e. infant mortality increases), but once we introduce all the relevant controls the effect of $ExportShock_{it}$ becomes insignificant. Column (5) replicates the specification of columns (2) and (4), but introduces both $PollutionExportShock_{it}$ and $ExportShock_{it}$. The coefficient on $PollutionExportShock_{it}$ remains very similar once we control for $ExportShock_{it}$. The coefficient on $ExportShock_{it}$ is negative, but in most specifications the standard errors are very large. The correlation between the two variables $PollutionExportShock_{it}$ and $ExportShock_{it}$ is 0.74, but this does not seem to result in a collinearity problem.[28] In column (6), in order to address the concern that regions initially specialized in dirty industries may be on a different trajectory for infant mortality, we control for the average initial pollutant emissions implied by the start-of-the-period employment structure, i.e. $PollEmployment^p_{it}$ as described by equation (10). The addition of this variable does not affect our coefficients of interest and confirms that *PollutionExportShock* captures the effect of a focus on dirty industries that *also* experience an export expansion. Column (7) replaces Region×Year dummies with Province×Year dummies, thereby reducing the amount of variation in the export shocks and the coefficient of interest. The last three specifications all find a negative, but not always significant effect of the variable $ExportShock_{it}$, which captures the effect of export expansion on local income and therefore health outcomes.

We now comment on the magnitude of these effects. One extra pound per worker of SO_2 raises IMR by 0.317-0.537 extra deaths per thousand live births depending on the specification. Due to its ability to better account for local changes in unobservable variables, our preferred specification is in column (7). Because the magnitude of this shock varies by decades, it is worth explaining the resulting effects separately. A one standard deviation increase in $PollutionExportShock^{SO2}$

[28]Some readers have suggested that introducing two variables that are correlated may result in both variables displaying a significant coefficient, but of opposite sign. We simulated a dataset similar to ours in terms of number of observations and correlation of the two variables of interest. We repeated the simulation 500 times and found that correlation among the two variables does not result in systematically biased coefficients. Simulation details available upon request.

in the 1990's brings about 1.1 extra deaths per thousand births (5.9% of a standard deviation in IMR change over the same period). The equivalent number for the 2000's is 2.5 extra infant deaths per thousand births (17.5% of a standard deviation in IMR change over the same period). Using the statistically insignificant estimate in column (7) of Panel A to measure the effect of *ExportShock* on mortality, we find that a 1990's standard deviation increase in export per capita causes 0.05 fewer deaths per thousand births, while the equivalent effect for a 2000's standard deviation is 0.48 fewer deaths per thousand live births. We will evaluate the robustness of these results to additional considerations in section 7.

6.2.1 Alternative Measures of External Demand Shocks

In this section, we demonstrate the robustness of the basic results to many alternative measures of external demand shocks. The results are reported in Table 4.

Output shocks. If economies of scale are an important feature in many sectors, then a positive demand shock coming from abroad may result in a decline in average costs and an increase in the amount of output produced. Therefore it makes sense to confirm the result when we employ the value of output and its pollution content as a measure of the shock. For the period 2000-2009 we have prefecture-level data on output, instead of just exports, so we replace exports with total production and create a *PollutionOutputShock* and an *OutputShock*, but still adopt the same IV strategy described in section 5.2. The result in column 1 of table 4 is in line with the ones in Table 3.

Input-output Relation Adjusted Shocks. One may be concerned that external demand shocks may induce production expansion of intermediate goods, and as a result extra emissions of pollutant. In particular, our measure will understate the pollution shocks in the prefectures specializing in dirty intermediate goods. To alleviate this concern, we use the information from China's input-output tables and construct alternative pollution export shock and income export shock as follows:[29]

$$PollutionExportShock_{it}^{p,IO} = \sum_k \gamma_{kt}^p \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta Y_{Ckt}}{L_{Ck,t-1}} ,$$

$$ExportShock_{it}^{IO} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta Y_{Ckt}}{L_{Ck,t-1}} .$$

[29] We use the 1997 input-output table to construct export shocks over 1992-2000 and the 2007 input-output table to construct export shock over 2000-2010. Results remain similar if we use the 1997 input-output table to construct export shocks for both decades. More details can be found in the Appendix A.

ΔY_{Ckt} is the component of industry k of the vector $(\mathbf{I}-\mathbf{C})^{-1}\mathbf{\Delta X_{CRt}}$, where $\mathbf{I}$ is an identity matrix, and $\mathbf{C}$ is the matrix of input-output coefficients and $\mathbf{\Delta X_{CRt}}$ is the vector of industry export expansion during the period t. We also construct the corresponding instruments $\widehat{PollutionExportShock}_{it}^{p,IO}$ and $\widehat{ExportShock}_{it}^{p,IO}$ by replacing $\mathbf{\Delta X_{CRt}}$ with tariff-predicted export growth $\mathbf{\Delta \widehat{X}_{CRt}}$. Aligned with our baseline results, column (2) shows that pollution export shocks has a significantly positive effect on IMR, while the estimated coefficient of income export shock is statistically not different from zero. In addition, we find that a standard deviation increase in $PollutionExportShock_{it}^{IO}$ of SO_2 increases IMR by 2.8 per thousand of live births, which magnitude is similar to our baseline findings.[30]

Export-Share-Weighted Shocks. Due to data limitation, in section 5.1, we employ industry employment share to proxy for a prefecture's export share to construct the baseline export shocks. As a sensitivity test, in this subsection, we use a prefecture's export share in 2000 to construct the theoretically consistent measures, that is:

$$PollutionExportShock_{it}^{p,Ex} = \sum_k \gamma_{kt}^{p} \frac{X_{iRk,t-1}}{X_{CRk,t-1}} \frac{\Delta X_{CRkt}}{L_{i,t-1}} \ ,$$

$$ExportShock_{it}^{Ex} = \sum_k \frac{X_{iRk,t-1}}{X_{CRk,t-1}} \frac{\Delta X_{CRkt}}{L_{i,t-1}} \ .$$

The instruments $\widehat{PollutionExportShock}_{it}^{p,Ex}$ and $\widehat{ExportShock}_{it}^{Ex}$ are constructed similarly with ΔX_{CRkt} replaced by $\Delta \hat{X}_{CRkt}$. Column (3) shows that our main findings are not sensitive to these alternative measures. In particular, we find that over 2000 to 2010, IMR will increase by 2 per thousand of live births when a prefecture is hit by a standard deviation of (export weighted) SO_2 pollution export shock.[31]

Principal Component Adjusted Shocks. Our baseline analysis studies the effect of export pollution shock on IMR for each pollutant individually. One concern is that emission intensities of different pollutants are positively correlated. As a results, the estimated effect of one pollutant could pick up the adverse effects of other pollutants. To help address this concern, we extract the principal component from the emission intensities of SO_2, TPS, and NO_2, and construct alternative measures as follows:

$$PollutionExportShock_{it}^{PCA} = \sum_k \gamma_{kt}^{PCA} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{CRkt}}{L_{Ck,t-1}} \ ,$$

[30] The standard deviation of $PollutionExportShock_{it}^{SO_2,IO}$ is 38.2 over the period 1992 to 2010.

[31] The standard deviation of $PollutionExportShock_{it}^{SO_2,Ex}$ is 16.2 over the period 2000 to 2010.

where γ_{kt}^{PCA} is the score predicted by the first component.[32] The instrument $Pollution\widehat{Export}Shock_{it}^{PCA}$ is constructed accordingly. The estimate reported in column (4) suggests that a standard deviation increase in $PollutionExportShock_{it}^{PCA}$ is associated with 4.8 extra deaths per thousand of births.[33]

Export Expansion by Industry Group. As discussed in Section 2.3, we employ the data on pollution intensity from the US to impute China's 3-digit industry pollution intensity. A potential concern is that an industry's emission intensity varies across countries and over time, due to different and changing abatement technologies. In this section, we use the information of industry pollution ranking and examine the effects of export expansion of different industry groups on IMR. Specifically, the CSIC industries are ranked according to the pollution intensity of SO2, and the ones belonging to the bottom and upper halves are classified into Clean and Dirty group, respectively.[34] The measures of local economy's export exposures to different pollution intensity groups are constructed according to

$$ExportShock_{it}^{K} = \sum_{k \in K} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{CRkt}}{L_{Ck,t-1}} ,$$

where K denotes the sector which industry k belongs to, and $K \in \{Clean, Dirty\}$. By construction, $ExportShock_{it}^{K}$ captures the exposure in dollar per worker to export expansion in sector K. The concern of measurement error in industry pollution intensity could be alleviated for two reasons. First, the relative pollution intensities across industries are likely to be inherent in the dissimilarities of production processes.[35] In other words, the ranking of pollution intensities is likely to preserve over space and time. Second, the grouping of industries effectively reduces the measurement errors introduced by a handful of industries. Nevertheless, these measures disregard the heterogeneity of emission intensities within clean and dirty industry groups.

We investigate the effects of export shocks of different pollution intensity groups on IMR by estimating the following equation:

$$\Delta IMR_{it} = \kappa_1 + \kappa_2 ExportShock_{it}^{D} + \kappa_3 ExportShock_{it}^{C} + \nu_{it} ,$$

where $ExportShock_{it}^{K}$ are instrumented by $\widehat{ExportShock}_{it}^{K}$ that are constructed accordingly. In column (5), we detect a significant effect of dirty export expansion on IMR. It is estimated that a 1000 USD $ExportShock^{D}$ increases IMR by 6.8 per thousand births. Moreover, we find a

[32] The first component explains 75.5% of variance in the 1990s, and 87.9% in the 2000s.
[33] The standard deviation of $PollutionExportShock_{it}^{PCA}$ is 0.55 over the period 1992 to 2010.
[34] Our results are consistent when industries are grouped into tertiles, i.e., Clean, Medium and Dirty.
[35] For example, the production of steel is dirtier than electronic products in both 90's and 00's, and in both China and US.

significant effect of clean export expansion on IMR, with a 1000 USD $ExportShock^C$ reducing IMR by 1.7 per thousand births. These counteracting effects illustrate that the effect of export on pollution depends on whether expansion is concentrated in dirty or clean sectors.

Change in Employment Share by Industry Group. Lastly, we examine the effect of employment growth in clean and dirty sector on IMR. The analysis is conducted at 2-digit CSIC level, because the prefecture-level employment data are not available at 3-digit CSIC level in 2010. A prefecture's change in employment share in clean and dirty sectors are constructed as follows: $\Delta EmpShare_{it}^K = \sum_{k \in K} \frac{\Delta L_{ikt}}{L_{i,t-1}}$, where $K \in \{Clean, Dirty\}$. Column (6) reports the regression results with $\Delta EmpShare_{it}^K$ instrumented by $\widehat{ExportShock}_{it}^K$. Consistent with the finding in column (5), we find that employment expansion in dirty sector increases IMR while employment expansion in clean sector lowers it.

6.3 Results for Specification 2: Pollution Concentration Channel

So far we explored the "reduced form" effect of export shocks on mortality, but we have ignored the channels through which exports shocks operate. In this section we explore the effect that export shocks have on mortality through pollution concentration as summarized by equations (13) and (14) and the diagram in Figure 3. Both equations are estimated by instrumental variables employing the instruments described in section 5.3. Table 5 reports the results of the first stage regression, i.e., the effects of the two types of export shocks on the air concentration of SO_2 (Panel A) and $PM2.5$ (Panel B). We find that $PollutionExportShock$ has a positive and significant effect on pollution concentration for both pollutants, while $ExportShock$ has a negative effect on pollution, but the effect is often not statistically significant. The set of controls and fixed effects are analogous to Table 3. According to column (3) of Panel A, a one 2000's standard deviation increase in $PollutionExportShock$ causes SO_2 concentration to rise by an additional 6.3 $\mu g/m^3$, while a one 2000's standard deviation increase in $ExportShock$ causes concentration to fall by 1.9 $\mu g/m^3$ (not statistically significant).

In Table 6 we explore the effect of pollution concentration on infant mortality, still allowing for export shocks to have a separate effect on IMR through the effect of export shocks on income. Notice that in this table we report, for comparison with other studies, the OLS estimates of the relationship between mortality and pollution concentration. Columns 1 and 3 show that such correlation is not significantly different from zero, a result that is easily explained by the fact that a rise in pollution concentration can be due for example to positive productivity shocks. Such productivity shock could induce an increase in economic activity thereby raising emissions, but it could also improve health outcomes through increased expenditure in nutrition and healthcare facilities. Nevertheless, we find a significant and positive effect of the change in pollution concentration on mortality once we adopt an IV approach. This is because our system of equations (13) and (14) addresses two issues: (i) it provides an instrument for $\Delta PollConc^p_{it}$ that is $PollutionExportShock$ which affects infant mortality only through its effect on pollution; (ii) it allows $ExportShock$ to have an effect on mortality both through pollution and directly. We find the same pattern in the OLS and IV coefficient estimates for both pollutants SO_2 and $PM2.5$. Because the link between pollution concentration and infant mortality has been estimated by other studies, to make our results comparable, we express them in terms of elasticities. We find that the elasticity of IMR to $PM2.5$ to be 2.1, while the elasticity of IMR to SO_2 is 0.9. Table 7 reports estimates from other studies to facilitate comparison.

Our estimate of the elasticity of IMR to SO_2 concentration is quite similar to the one estimated for China by (Tanaka, 2015) which is 0.82. There is no direct comparison for the elasticity of IMR to PM2.5 and our estimate of 2.1 is higher than estimates based on TSP and $PM10$. We believe this higher elasticity is justified by the higher risk of damage caused by fine particulate matter which is capable of penetrating more deeply in the lungs. The stronger effect of fine particulate matter is documented in (Pope III et al., 2002). Although not directly comparable, a handful of cross-sectional studies on the impact of TSP on total adult mortality in China provide a useful benchmark. As summarized by Cropper (2012) these studies report semielasticities and find that for every 1 $\mu g/m^3$ increase in PM_{10} the risk of dying increases by 0.12%-0.15%. By using the conversion $PM_{2.5} = 0.6PM_{10}$ that Cropper employs our results imply that for every 1 $\mu g/m^3$ in PM_{10} infant mortality rate increases by 3.6% (relative to the average). The effect we estimate is stronger than the cross-sectional studies summarized by Cropper, a fact that we attribute to a plausibly higher sensitivity of infant health to pollution, but most importantly to the panel structure of our study (our study employs decade differences which allow to control for prefecture-specific levels) and to our attempt to cleanly identify the causal effect of pollution of mortality. If we were to limit ourselves to the OLS coefficient we would find no effect or even an effect of the opposite sign.

6.4 Effects of Pollution on Infant Mortality by Cause of Death

In this section we provide additional evidence to corroborate the finding that the increased mortality we detect is indeed due to pollution. We employ a source of data that has been previously explored in Chen et al. (2013) to measure the effect of increased pollution due to coal-fueled heating on mortality in China. Because we only have data for 117 prefectures for the first decade, we cannot include the same rich set of fixed effects as we did in Table 3. We still include region fixed effects and control for pollution implied by initial industrial composition $PollEmployment$.

In Table 8 we report the estimates for $PollutionExportShock$ using SO_2 as pollutant, but the appendix reports the equivalent tables for TSP and NO_2. We find that only mortality due to cardio-respiratory causes is sensitive to the pollution content of export. Infant mortality classified as related to digestive, infectious, external and infant-specific causes do not appear to be sensitive to export shocks. These results reassure us that we are finding the effects where it is reasonable to expect them.

7 Robustness

In this section we return to the baseline "reduced form" results of table 3 and introduce a number of control variables that account for several potential confounding factors. Each column of Table 13 is discussed in the following sections and while this table employs $PollExportShock^{SO2}$, appendix tables A.5 and A.6 perform the same robustness checks for other sources of air pollution. The analogous robustness tests for the link of export shocks and pollution concentration are discussed in Appendix D.1.

7.1 Robustness: Neighboring Shocks and Wind Direction

In Table 9 we consider the impact of export shocks experienced by neighboring prefectures. In principle there are at least two channels through which export shocks can affect neighboring prefectures. The first one is through intermediate goods. If a neighboring prefecture of prefecture i experiences an increase in exports, it will increase its demand for intermediate inputs, some of which may come from prefecture i and could in turn generate extra production and therefore pollution and adverse health consequences in prefecture i. The other possibility is that pollution generated in nearby prefectures may simply be transported by wind to other areas. In order to capture these effects we construct two variables, which are explained in detail in Appendix A. The variable $PollutionExportShock_{it}^{p,N}$ is an average of the shocks experienced by prefectures that share a border with prefecture i. In order to measure the effect of wind-transported pollution, variable $WindPollutionExportShock_{it}^{p,N}$ gives a larger weight to neighboring prefectures that are upwind relative to prefecture i. If the intermediate channel is the only one active, then $WindPollutionExportShock_{it}^{p,N}$ should not affect mortality in i once we control for $PollutionExportShock_{i,t}^{p,N}$. The regression results are presented in Table 9. As shown in columns (1) and (2), regardless of the weight, a positive neighboring export pollution shock is estimated to have significantly positive effect on IMR. More importantly, the estimates of the coefficients for local shocks remain similar to those of the baseline regression. This finding suggests that the local pollution affect IMR independently of cross-border spillovers. The regression in column

(3) includes both measures of neighboring shock. We find that $WindPollutionExShock^{p,N}$ has significantly positive effect on IMR, while the estimated coefficient of $PollutionExportShock^{p,N}$ becomes insignificant. We take this finding as suggestive evidence that the neighboring pollution shock affects IMR by bringing in wind-borne pollutants. Columns (4) and (5) repeat the regressions in Columns (2) and (3), with $WindPollutionExportShock^{p,N}$ constructed using the information from the two nearest weather stations instead of the nearest. The results remain robust.

7.2 Robustness: Future shocks

As we have already mentioned, one of the drawbacks associated with the Bartik approach is that the initial industrial composition may be correlated with other unobserved characteristics that also affect infant mortality. More concretely, we may be concerned that prefectures initially highly specialized in polluting sectors may have already been experiencing relatively higher increases in child mortality because, for example, they had a more lax enforcement of environmental regulation. Aside from pre-trends controls which we have introduced previously, here we perform a falsification exercise where we regress the current change in IMR on future shocks. Table 10 finds no correlation between IMR and future shocks and moreover the sign is reversed relative to our main regression in Table 3. This finding suggests that prefectures hit by larger export shocks were not already experiencing relatively faster increase in mortality rates.

7.3 Robustness: Mortality by Gender

Table 11 investigates the effects of export expansion on IMR by gender, using the specification of Column (5) in Table 3. The results are qualitatively similar for both genders, which is consistent with a priori that air pollution harms infant's health indiscriminately. Quantitatively, however, it is found that the effects on girls are larger in magnitude than boys. One possible explanation is that in the context of China, due to the traditional preference for boys, parents could be more likely to take measures to minimize a newborn son's exposure to pollution or to seek medical treatment for his illness. This echoes the findings in Jayachandran (2009) that the air pollution caused by wildfires in Indonesia had larger adverse effect on the mortality of newborn girls than boys.

7.4 Robustness: Mortality of Young Children Aged 1-4

Table 12 examines the effect of export expansion on the mortality in early childhood. We follow the specification (9), but replace the dependent variable with change in mortality rate (MR) of children aged 1-4. Column (1) shows that one extra pound per worker of SO_2 increases MR of the age 1-4 by 0.037 per thousand. Moreover, it is estimated that 1000 USD export expansion reduces MR of age 1-4 by 0.11 per thousand. The coefficients of both $PollutionExportShock^{SO2}$ and $ExportShock$ are significant at 1% level. Due to the lack of data on mortality rate of children aged 1-4 from the 1982 census, we are not able to control for the pre-trends of MR for the full sample. Column (2) includes the quadratic terms of change in IMR in the previous decade, which in effect account for the common secular trends of IMR and MR in the early childhood. The coefficients of interest change little.[36] Columns (3)-(4) and (5)-(6) present the consistent results for TSP and NO_2, respectively.

7.5 Energy Production

The analysis so far has employed, in constructing our $PollutionExportShock$, data that only accounts for the direct emissions generated in the production process, but it does not include emissions due to the generation of electricity needed for production. The reason why only direct emissions are usually included in the intensity measures is that one would need to know the source of the electricity and that depends on the region where firms are located, regardless of the industry. For our purpose, if electricity generation is not accounted for in our pollution export shock, we may be under-estimating the increase in pollution due to export expansion. At the same time, electricity generation may happen in other provinces and sufficiently far from where production takes place, so that its effect will not be felt in the prefecture where the export-induced demand for power is arising.[37] In order to address these concerns, we introduce a control at the prefecture level which is the amount (also measured in dollar value of output per worker) of electricity generated by fossil fuel. The magnitude and significance of the $PollutionExportShock$ is not affected, but we find that expansion in energy production, is a significant predictor of increases in infant mortality.

7.6 Imports

We have so far disregarded imports in accounting for the link between trade, pollution and mortality. There are three reasons for this asymmetry of treatment. First, China's trade surplus has grown considerably over 1990-2010 from 5.5 billions to 336 billions, implying the gap between exports and imports has widened.[38] The second reason is that, in principle, increase import

[36] We verify that the results remain robust if we restrict the sample to years 2000 and 2010 and control for the quadratic terms of change in MR for age 1-4 in the previous decade.

[37] As an example, in 2008 around 40% of the electricity in Guangdong was imported from outside the province. (China Energy Statistical Yearbook, 2009)

[38] Autor et al. (2013) also focus on imports from China to the US due to the large and growing trade imbalance between the two countries.

inflows may have two distinct effects on pollution. If imports replace local production, then increased imports would likely reduce pollution and mortality, but if imports are concentrated in intermediate inputs, then a surge in imports may spur further local production and cause pollution. The third reason is that, while we are reasonably confident about the exogeneity of changes in tariffs faced by Chinese exporters, import tariffs established by China are unlikely to be uncorrelated with other industry factors that cause pollution. Despite all these considerations, we present a specification where we introduce a $PollutionImportShock$, constructed analogously to our $PollutionExportShock$ by replacing export value with import value. Column (2) of Table 13 finds a significant negative effect of $PollutionImportShock$ on mortality, which provides suggestive evidence for the import substitution channel.

7.7 Other Controls

In column (3) we control for a prefecture-level variable $HighSkillShock$, introduced by Li (2015), which measures the extent to which export expansion increases demand for high skill workers.[39] The concern is that what $PollutionExportShock$ is capturing expansion in low-skill industries (rather than dirty ones) and that this may be correlated with enforcement of environmental regulations, if regions with more educated workers demand higher environmental standards. Although this scenario seems to be confirmed in the data, our coefficient of interest is not affected. In column (4) we introduce two variables that capture the role played by SOEs (state-owned enterprises) as studied by Dean et al. (2009). We confirm their findings in that the share of SOEs is positively correlated with increases in mortality, while the share of foreign firms is not. While we cannot exclude other channels that link these variables, our findings are consistent with the logic that SOEs are subject to less stringent controls and therefore may be disproportionately responsible for increased pollution. In column (5) we introduce a variable that captures differences in environmental regulation due to the Two Control Zones (TCZ), as described by Tanaka (2015). Our finding of a positive relationship between mortality and the TCZ dummy is consistent with the view that those stricter environmental regulations were introduced in more polluted cities.

8 Discussion and Concluding Remarks

In the 20 years between 1990 and 2010 China experienced a tremendous increase in its exposure to international trade. China's exports went from 62 billion USD in 1990 to 1.5 trillion USD in

[39] The high-skill export shock is constructed as $HighSkillShock_{it} = \sum_k \zeta_{k,t-1} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{CRkt}}{L_{Ck,t-1}}$, where $\zeta_{k,t-1}$ is the start-of-the-period skill intensity of industry k measured by the share workers with high school education or above. The instrument $\widehat{HighSkillShock}_{it}$ is constructed by replacing ΔX_{CRkt} by $\Delta \widehat{X}_{CRkt}$.

2010, while its trade surplus went from 8.7 billion in 1990 to 336 billion USD in 2010. Even as a share of GDP, trade surplus has been increasing over time: it was 2% in the 1990s and almost 6% in the 2000s. In this paper we ask whether this export boom generated additional pollution that affected health outcomes during the same period. We are particularly interested in isolating the effect of increased demand from abroad due to the reduction in trade barriers because export expansion can be due to a number of factors, among which productivity changes. Why are we disregarding productivity changes? This is because those shocks would also increase exports, but it would be hardly appropriate to attribute their environmental and health consequences as due to trade. The thought experiment we have in mind is to hold technology constant and consider only export expansion due to increased demand from countries that now impose lower tariffs on goods coming from China. Our identification strategy relies on two components: i) we instrument export expansion with tariff reductions faced by Chinese exporters; ii) we exploit initial differences in the industrial composition of different prefectures to construct local export shocks.

We find that the pollution content of export affects mortality. Take two prefectures within the province Jiangsu, north of Shanghai: Zhenjiang experiences an $PollutionExportShock$ larger than Taizhou by about a standard deviation. Our estimates imply that Zhenjiang sees its infant mortality increase relative to Taizhou by 1.1 and 2.5 extra deaths per thousand live births respectively in the 1990s and 2000s because of export expansion. This is equivalent to about 15% of the variation in decline in IMR across prefectures. In fact during the 2000s Zhenjiang's IMR declined by less than Taizhou's IMR[40]. We find that the reason why mortality increases is that $PollutionExportShock$ affects concentration of air pollutants: our estimates again imply that Zhenjiang sees an increase in $PM2.5$ concentration by 1.7 $\mu g/m^3$ (about 17% of the standard deviation of $PM2.5$ change over the period) relative to Taizhou. We find that the dollar-value export shock has the opposite sign and tends to decrease infant mortality and pollution, although it is less often significant. We nevertheless believe it is instructive to gauge the size of these two shocks, $PollutionExportShock$ and $ExportShock$ in order to assess their combined effect on the decline in IMR in different prefectures. Because we have more confidence in our specifications with province fixed effects, we perform this exercise for all prefectures in a given province. To save space we report only the exercise for 6 large provinces that we pick due to their size and economic significance, although they represent different industrial orientations. The 6 provinces are Guangdong, Hebei, Henan, Jiangsu, Sichuan, and Liaoning and the results of the exercise are reported in figure 6. The figure reports, for each prefecture, the value of $\hat{\alpha}_2 PollutionExportShock^p_{it} + \hat{\alpha}_3 ExportShock_{it}$ from specification 9 in column 7 in table 3 using the value of the shocks for the period 2000-2010. We can see that within those 6 provinces there is wide heterogeneity in the impact of export shocks on mortality.

[40]The infant mortality rate actually declined by 6.8 in Zhenjiang and by 8.8 in Taizhou

We have purposely emphasized that our identification strategy based on differences across prefectures in export exposure is meant to identify only the relative differences in mortality across prefectures caused by pollution induced by trade. It is important to remember this limitation because it could be the case that the overall income growth in China due to trade has brought about demand and the means for stricter enforcement of environmental laws. Although we still believe that this is the correct interpretation, we can nevertheless perform the following exercise assuming away *aggregate effects* at the level of China as a whole. What follows is a quantitative assessment of the effects we have analyzed, but now applied to the entire country and the whole time period. For the period 1990-2000, with an average number of births of 55,723 per prefecture per year, our calculations imply that $PollutionExportShock$ caused a total of 66,064 extra deaths.[41] For the period 2000-2010, when the export shocks in dollar terms are ten times those in the 1990s, the same calculation yields an additional 179,409 infant deaths. Although the effect of $ExportShock$ is not always significant, we still employ it to quantify its beneficial effect on mortality. The effect of $ExportShock$ reduced the number of deaths by 3,075 in 1990-2000 and by 21,632 in 2000-2010. The net effect expressed in percentage was an increase in mortality by 0.032 and 0.113 percentage points. As a reference, Currie and Neidell (2005) find that the decline in carbon monoxide in California over the 1990s caused a reduction in infant mortality of 0.02 percentage points. So our estimate is similar to theirs for the 1990, but about 5 times larger in the 2000s, which is reasonable since exports grow at an extraordinary pace during that period. Our effect is much smaller (for the 2000s it is about one tenth) relative to the one found by Jayachandran (2009) of an increase in mortality by one percentage point due to Indonesian wildfires.

The main take-away from this paper is that China might have greatly benefited from increased access to world markets, but some regions bore a disproportionate cost of this rapid export expansion in terms of higher infant mortality due to their more rapidly deteriorating environmental quality. This paper represents a first attempt to quantify the extent of the extra burden born by those regions that specialize in highly polluting products because of comparative advantage.

[41] This number is calculated by multiplying the average $PollExportShock$ of 2.2 by the coefficient 0.317 and the number of births 55723. The number is then divided by 1000 because mortality is expressed relative to 1000 live births. The resulting number is multiplied by 10 years and the number of prefectures (340) and finally divided by 2 because the export shock is calculated over a 10 years period and we assume that the increase happened in equal increments over the 10 years.

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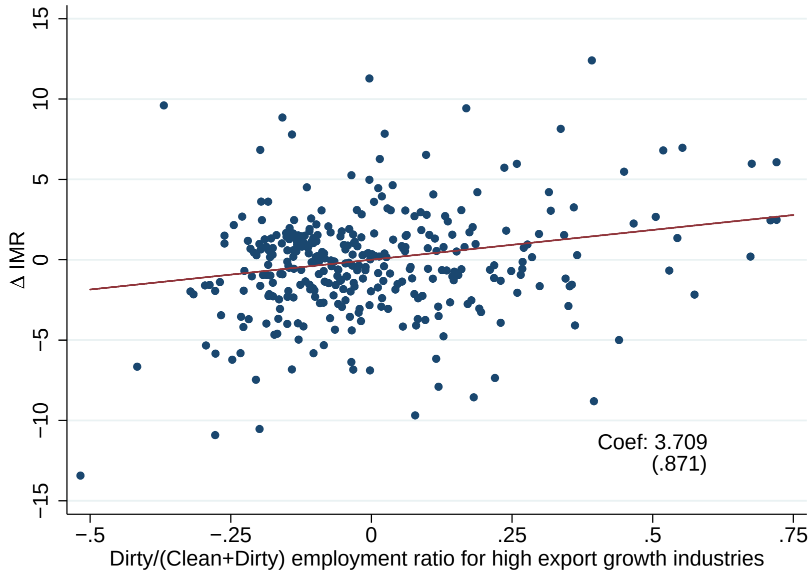
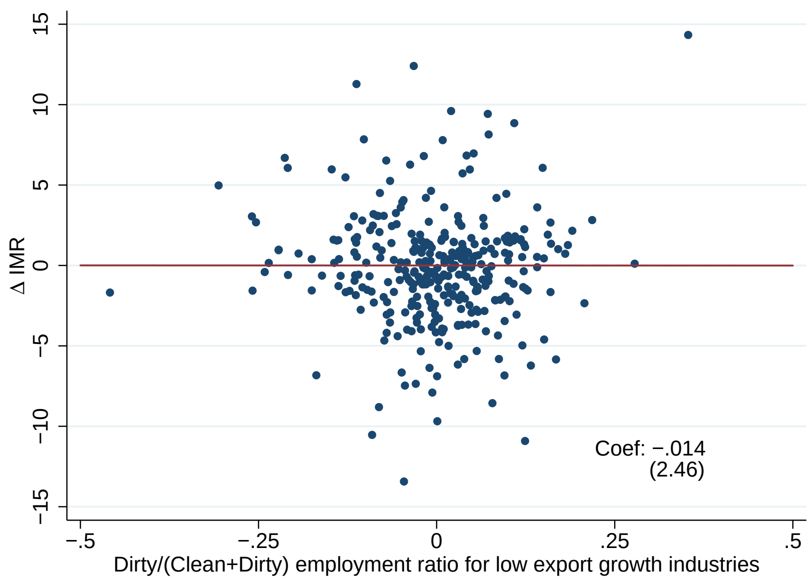
Figure 1: Change in IMR between 2000-2010 versus Specialization in 2000

Panel A: High Export Growth Industries

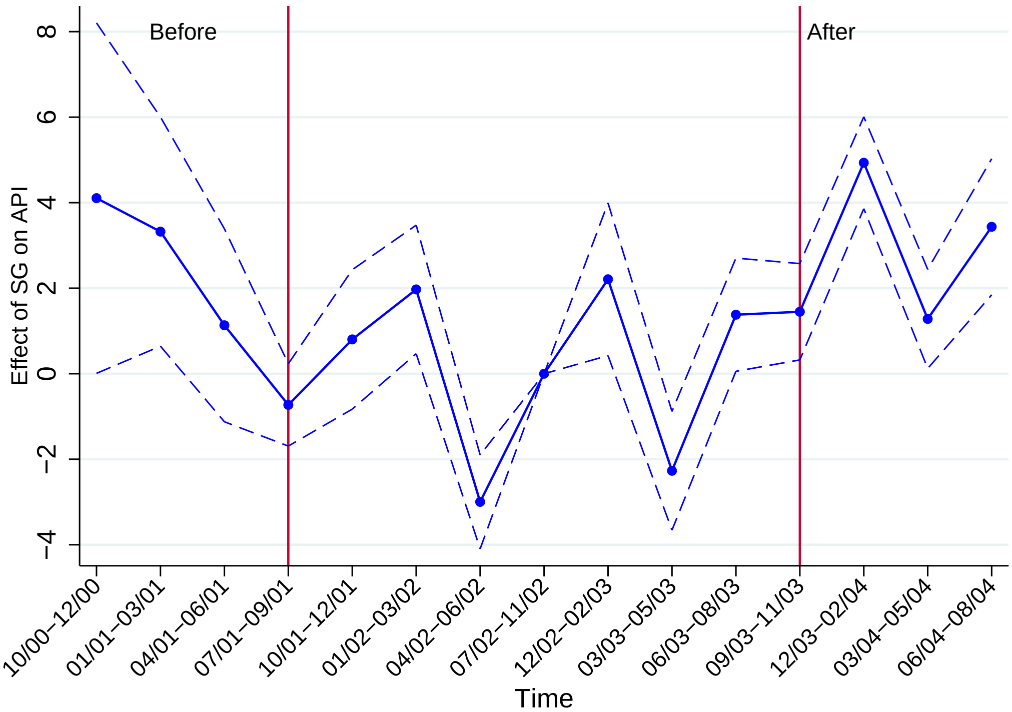


Panel B: Low Export Growth Industries



Notes: Panels A and B are added variable plots controlling for the start of the period IMR. Panel A shows the correlation between change in IMR and employment share dirty industries among industries with high export growth. Panel B shows the correlation between change in IMR and employment share dirty industries among industries with low export growth.

Figure 2: Air Quality Before, During and After the Steel Safeguard



Note: The figure reports coefficients δ_τ estimated from regressing daily air pollution measure API_{it} in prefecture i on an interaction between the initial share of employment in steel-related industries in that prefecture, $Share_i$, and a quarter dummy $Quarter_t^\tau$ controlling for prefecture fixed effects and region-year-month fixed effects according to the following specification:

$$API_{it} = \sum_\tau \delta_\tau Share_i \times Quarter_t^\tau + \phi_i + \psi_{rym} + \varepsilon_{it}.$$

The coefficients of interest and are estimated relatively to the omitted group (07/2002 to 11/2002).

Figure 3: Mechanism relating Export Shocks to Mortality

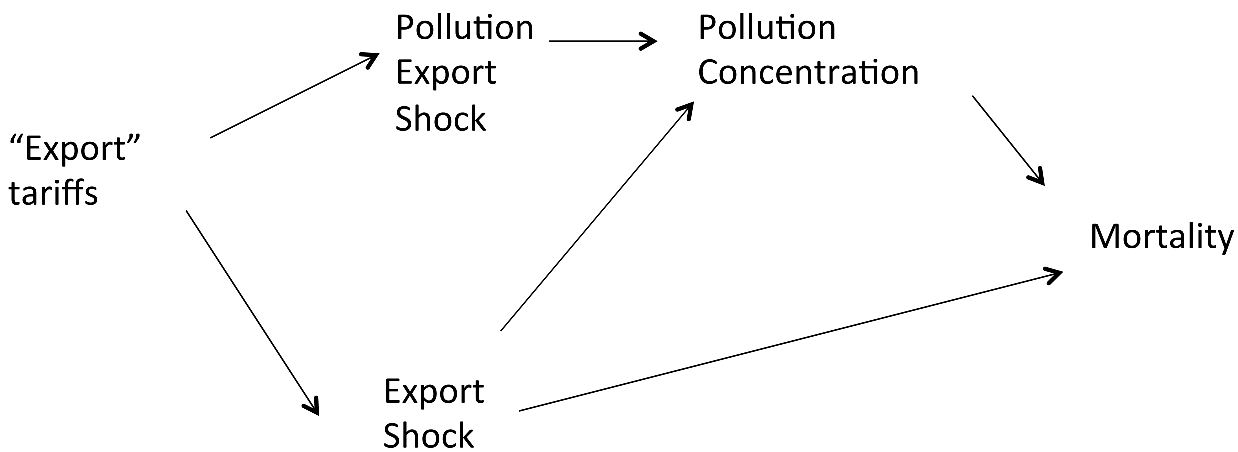
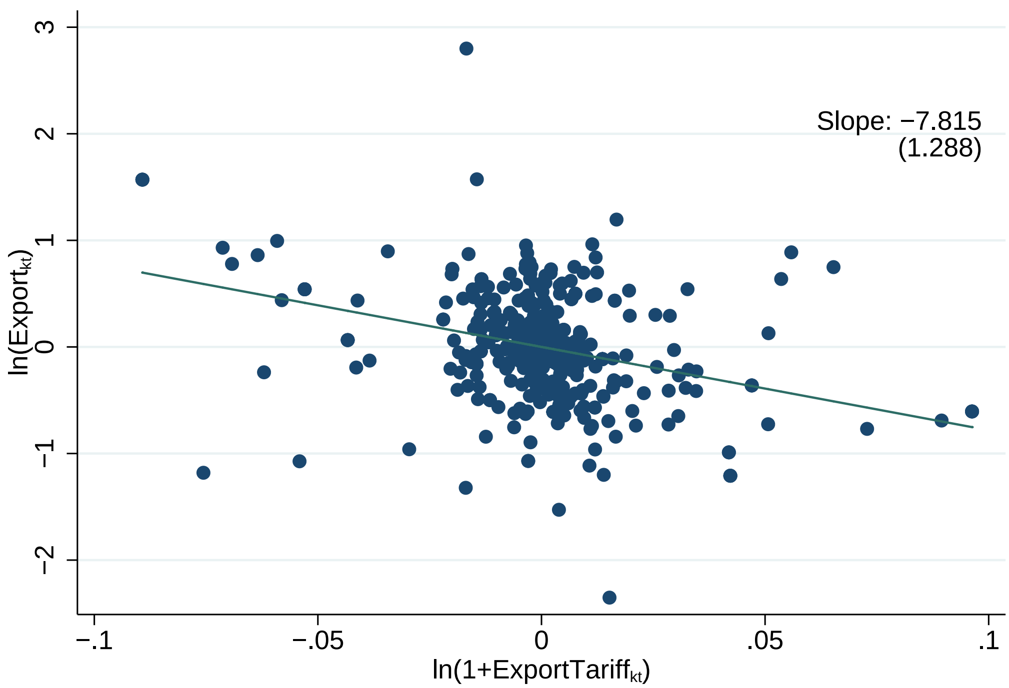


Figure 4: The relationship between Log(Exports) and Log(1+ExportTariff)



Note: Both axes report residuals of the variable regressed on time and sector fixed effects

Figure 5: Distribution of Export Pollution Shocks over Decades, SO2

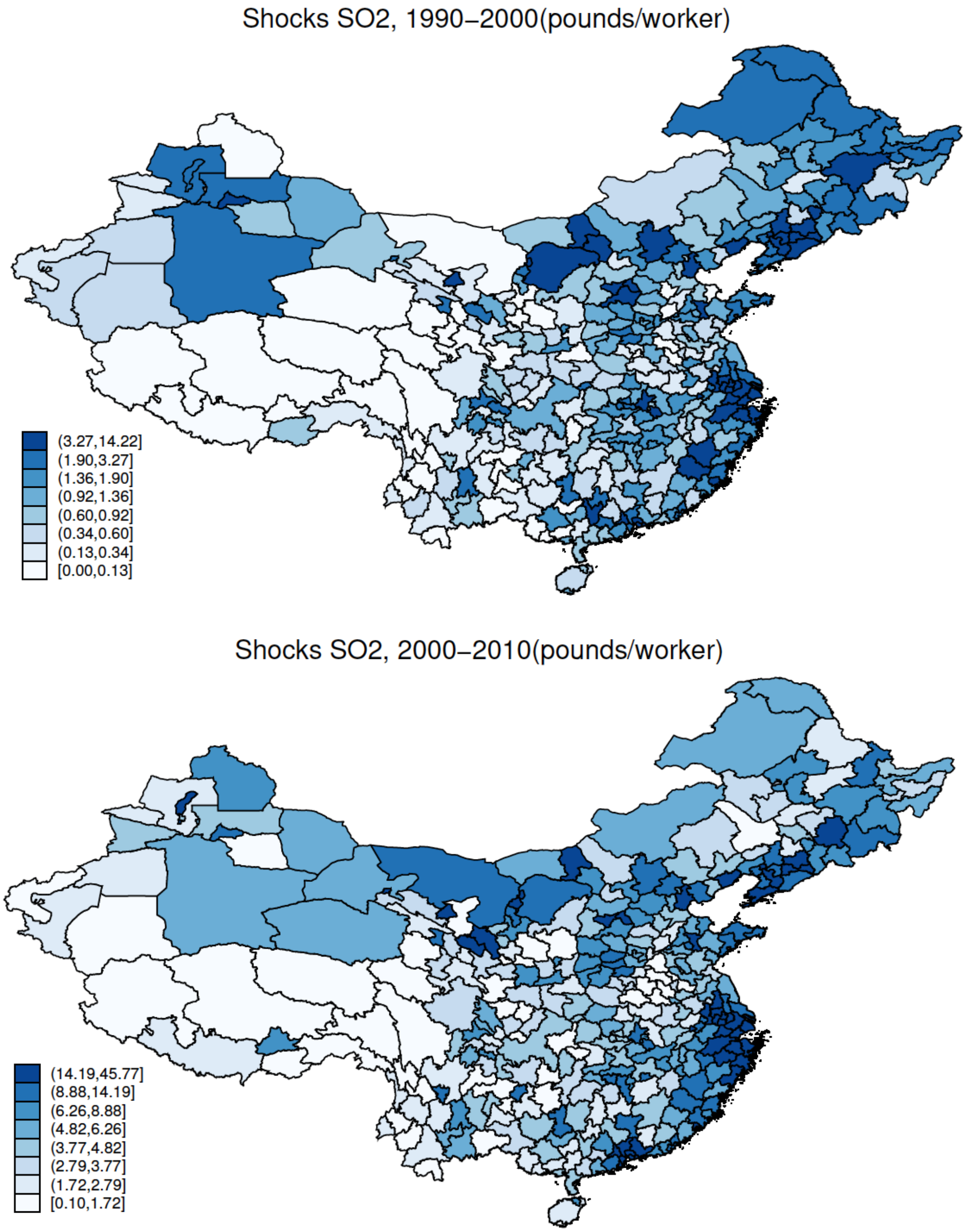
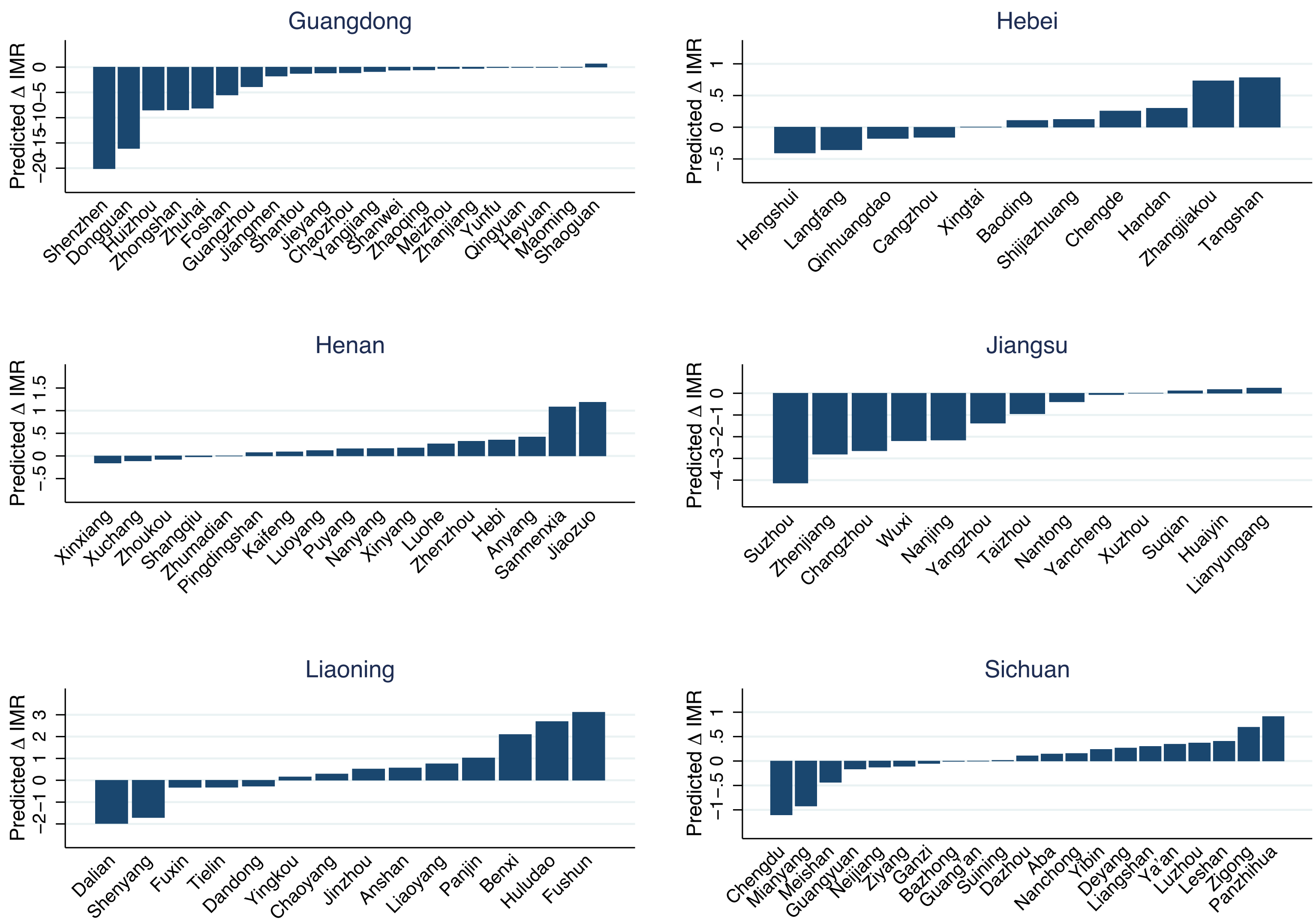


Figure 6: The combined effect of $PollutionExportShock_{it}$ and $ExportShock_{it}$ on IMR



Notes: Each bar represents for each prefecture the predicted change in IMR, i.e.$\hat{\alpha}_2 PollutionExportShock^p_{it} + \hat{\alpha}_3 ExportShock_{it}$, from specification 9 in column 7 in table 3 using the value of the two shocks for the period 2000-2010.

Table 1: Effects of 2001-03 Steel Safeguards on API

Dep. Var: API	(1)	(2)	(3)	(4)	(6)	(7)
$Before \times Share$	2.518**	2.592**				
	(1.059)	(1.048)				
$After \times Share$			1.628***	1.540***		
			(0.513)	(0.556)		
$NoSG \times Share$					2.553***	2.534***
					(0.465)	(0.498)
Prefecture	Y	Y	Y	Y	Y	Y
Year×Region	Y	Y	Y	Y	Y	Y
Month×Region	Y	Y	Y	Y	Y	Y
Time Window	07/00 – 09/02	07/00– 12/02	06/02– 05/05	03/02– 08/05	07/00– 05/05	07/00– 08/05
N	36,915	41,238	64,903	76,953	96,084	103,810
R^2	0.417	0.407	0.363	0.351	0.372	0.376

Note: Standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Summary Statistics

	mean	std	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Panel A: IMR (number of deaths per 1000 births)							
IMR, 1982	36.105	24.659	14.648	20.037	28.729	45.096	66.790
IMR, 1990	31.428	23.915	11.420	16.239	24.198	39.084	61.088
IMR, 2000	23.642	17.994	7.720	11.182	18.834	29.627	46.127
IMR, 2010	5.132	5.972	1.374	2.067	3.362	5.708	10.944
ΔIMR, 90-00	-7.786	18.709	-23.745	-13.759	-6.358	1.561	9.562
ΔIMR, 00-10	-18.510	14.455	-37.307	-23.704	-14.696	-8.748	-4.756
Panel B: Changes in Pollution concentrations(μg/m^3)							
$SO2$, 1992	86.354	76.636	20	39	64	104	173
$SO2$, 2000	43.445	38.757	12	19	31	55	92
$\Delta SO2$, 92-00	-41.459	55.883	-87	-55	-31	-9	0
$\Delta SO2$, 00-10	-5.624	33.235	-45	-14	1	14	23
$PM2.5$, 2000	34.156	19.662	10.857	18.327	31.603	48.369	61.311
$\Delta PM2.5$, 00-10	12.073	9.887	0.576	4.174	11.917	18.481	24.929
Panel C: Pollution Export Shocks (pounds per worker)							
$SO2$, 90-00	2.199	3.471	0.074	0.360	1.219	2.681	5.408
TSP, 90-00	2.133	2.915	0.091	0.374	1.229	2.624	5.164
$NO2$, 90-00	0.609	0.813	0.022	0.114	0.348	0.831	1.637
$SO2$, 00-10	8.109	7.996	1.582	2.984	5.494	9.997	18.540
TSP, 00-10	9.821	9.216	2.241	3.678	6.794	12.136	21.983
$NO2$, 00-10	2.768	2.788	0.517	0.984	1.889	3.457	6.699
Panel D: Export Shocks (1000 dollars per worker)							
ExShock, 90-00	0.151	0.220	0.004	0.019	0.072	0.178	0.423
ExShock, 00-10	1.440	2.223	0.217	0.399	0.785	1.532	3.100

Table 3: Change in Infant Mortality Rate and Shocks: 2SLS

Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: SO2							
$PollExShock^{SO2}$	0.449***	0.427***			0.537***	0.506***	0.317***
	(0.058)	(0.099)			(0.125)	(0.136)	(0.121)
$ExShock$			1.289***	0.373	-0.573	-0.500	-0.215
			(0.323)	(0.534)	(0.485)	(0.508)	(0.470)
Panel B: TSP							
$PollExShock^{TSP}$	0.424***	0.399***			0.461***	0.415***	0.255***
	(0.057)	(0.097)			(0.117)	(0.108)	(0.093)
$ExShock$			1.289***	0.373	-0.427	-0.330	-0.148
			(0.323)	(0.534)	(0.496)	(0.503)	(0.449)
Panel C: NO2							
$PollExShock^{NO2}$	1.442***	1.550***			2.318***	2.118***	1.383***
	(0.187)	(0.335)			(0.507)	(0.521)	(0.367)
$ExShock$			1.289***	0.373	-1.245**	-1.069*	-0.648
			(0.323)	(0.534)	(0.535)	(0.564)	(0.465)
Region×Year	Y	Y	Y	Y	Y	Y	
Initial Conditions		Y		Y	Y	Y	Y
Contemporary Shocks		Y		Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}		Y		Y	Y	Y	Y
$\sum_i \gamma_i^p \frac{L_{ijt-1}}{L_{jt-1}}$						Y	Y
Province×Year							Y
N	680	673	673	673	673	673	

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share and population density. Contemporaneous shocks include change in log GDP per capita, change in share of boys, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share, a dummy of provincial capital city and distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Change in Infant Mortality Rate and Shocks: Alternative Measures, SO_2 2SLS

Dep. Var: ΔIMR	Output Shocks (1)	IO adjusted Shocks (2)	Export Share Weighted Shocks (3)	PCA adjusted Shocks (4)	Export Shocks by Group (5)	Δ Emp. Share by Group (6)
$PollOutputShock$	0.188***					
	(0.066)					
$OutputShock$	-0.258					
	(0.473)					
$PollExShock$		0.072**	0.159**	8.774***		
		(0.028)	(0.045)	(2.140)		
$ExShock$		0.154	-0.723**	-1.034*		
		(0.346)	(0.327)	(0.529)		
$ExShock^D$					6.787***	
					(1.528)	
$ExShock^C$					-1.710***	
					(0.432)	
$\Delta EmpShare^D$						89.839*
						(48.811)
$\Delta EmpShare^C$						-14.449*
						(8.272)
Region×Year	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y
$\sum_i \gamma_i^{SO2} \frac{L_{ijt-1}}{L_{jt-1}}$	Y	Y	Y	Y	Y	Y
N	340	673	340	673	673	656
R^2	0.698	0.633	0.746	0.635	0.636	0.265

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Changes in Pollutant Concentration and Shocks: 2SLS

Dep. Var: Δ*Pollutant Concentration*	(1)	(2)	(3)
Panel A: $\Delta SO2$			
$PollExShock^{SO2}$	0.747***	1.050***	0.785**
	(0.249)	(0.254)	(0.353)
$ExShock$		-1.425*	-0.856
		(0.805)	(0.961)
N	268	268	268
Panel B: $\Delta PM2.5$			
$PollExShock^{TSP}$	0.203***	0.239***	0.181***
	(0.060)	(0.074)	(0.066)
$ExShock$		-0.721	-0.622
		(0.522)	(0.523)
N	340	340	340
Region($\times$Year)	Y	Y	Y
Initial Conditions	Y	Y	Y
Contemporaneous Shocks	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$			Y

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Changes in Infant Mortality Rate and Changes in Pollutant Concentration: 2SLS

	OLS	2SLS	OLS	2SLS
Dep. Var: ΔIMR	(1)	(2)	(3)	(4)
Panel A: SO2 Concentration and IMR				
$\Delta SO2$	-0.016	0.298**	-0.016	0.464*
	(0.033)	(0.150)	(0.034)	(0.278)
$ExShock$	-0.071	0.052	-0.071	-0.084
	(0.395)	(0.431)	(0.388)	(0.483)
N	268	268	268	268
Panel B: PM2.5 Concentration and IMR				
$\Delta PM2.5$	0.049	0.925*	0.044	1.454*
	(0.081)	(0.489)	(0.083)	(0.752)
$ExShock$	-1.552***	-0.777	-1.525***	-0.612
	(0.451)	(0.526)	(0.432)	(0.726)
N	340	340	340	340
Region(×Year)	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y
Contemporaneous Shocks	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$			Y	Y

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Elasticity of IMR to pollutant concentration in other studies

	Country	SO2	TSP	PM10
Arceo et al. (2015)	Mexico			0.42
Chay and Greenstone (2003a and b)	US		0.28-0.63	
Chen et al.(2013)	China		1.73	
Tanaka (2010)	China	0.82	0.95	

Table 8: Changes in Infant Mortality Rate and Shocks by Causes of Death: SO2, 2SLS

	Cardio-Respiratory		Infant Specific		Digestive	
Dep. Var: ΔIMR^{C}	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^{SO2}$	0.276***	0.459**	-0.318	-0.079	0.014	0.013
	(0.088)	(0.185)	(0.428)	(0.758)	(0.021)	(0.060)
$ExShock$		-2.571		-4.101		0.291
		(1.799)		(5.687)		(0.345)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^{p} \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

	Infectious		External Causes		Malnutrition	
	(7)	(8)	(9)	(10)	(11)	(12)
$PollExShock^{SO2}$	0.043	-0.010	-0.026	0.136	-0.013	-0.019
	(0.035)	(0.083)	(0.072)	(0.206)	(0.017)	(0.035)
$ExShock$		-0.444		-0.164		0.003
		(0.526)		(1.461)		(0.174)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^{p} \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

Notes: All regressions are weighted by total birth. All regressions start of period overall mortality rate, change in log GDP per capita, change in hospital beds per capita, and change in agricultural employment share. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Change in Infant Mortality Rate and Shocks:
Neighboring Shocks, 2SLS

		Nearest stations		Nearest two stations	
Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)
Panel A: SO2					
$PollExShock^{SO2}$	0.448***	0.399***	0.382***	0.410***	0.399***
	(0.129)	(0.123)	(0.121)	(0.123)	(0.122)
$ExShock$	-0.782	-0.779	-0.662	-0.777	-0.705
	(0.562)	(0.546)	(0.551)	(0.550)	(0.553)
$PollExShock^{SO2,N}$	0.312**		-0.393		-0.282
	(0.145)		(0.304)		(0.303)
$Wind\ PollExShock^{SO2,N}$		0.436***	0.808***	0.410***	0.680**
		(0.144)	(0.282)	(0.142)	(0.277)
Panel B: TSP					
$PollExShock^{TSP}$	0.383***	0.355***	0.344***	0.358***	0.350***
	(0.106)	(0.102)	(0.102)	(0.103)	(0.103)
$ExShock$	-0.635	-0.632	-0.531	-0.628	-0.561
	(0.543)	(0.517)	(0.516)	(0.518)	(0.522)
$PollExShock^{TSP,N}$	0.338**		-0.370		-0.271
	(0.146)		(0.300)		(0.298)
$Wind\ PollExShock^{TSP,N}$		0.438***	0.774***	0.420***	0.668**
		(0.143)	(0.294)	(0.141)	(0.285)
Panel C: NO2					
$PollExShock^{NO2}$	1.923***	1.741***	1.670***	1.778***	1.736***
	(0.552)	(0.529)	(0.525)	(0.529)	(0.531)
$ExShock$	-1.323*	-1.254*	-1.125*	-1.263*	-1.190*
	(0.692)	(0.651)	(0.666)	(0.657)	(0.672)
$PollExShock^{NO2,N}$	0.854**		-0.884		-0.578
	(0.427)		(0.770)		(0.783)
$Wind\ PollExShock^{NO2,N}$		1.157***	1.995***	1.094**	1.653**
		(0.436)	(0.735)	(0.446)	(0.780)
Region×Year	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y
N	673	673	673	673	673

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Change in Infant Mortality Rate and Future Shocks

	SO2		TSP		NO2	
Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^p_{t+1}$	-0.291	-0.138	-0.240	-0.011	-0.899	0.151
	(0.216)	(0.207)	(0.245)	(0.249)	(0.989)	(1.206)
$ExShock_{t+1}$		-2.033		-2.581		-3.130
		(2.337)		(2.489)		(2.433)
$\sum_k \gamma^p_{kt+1} \frac{L_{ikt+1}}{L_{it+1}}$	0.050	0.042	-0.053	-0.070	-0.076	-0.129
	(0.181)	(0.182)	(0.060)	(0.060)	(0.555)	(0.564)
N	333	333	333	333	333	333

Notes: All regressions are weighted by population of age 0. All regressions control for start of period overall mortality rate. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Change in Infant Mortality Rate and Shocks by Gender: 2SLS

	Boys			Girls		
	SO2	TSP	NO2	SO2	TSP	NO2
Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^p$	0.440***	0.343***	1.859***	0.588***	0.490***	2.401***
	(0.131)	(0.099)	(0.476)	(0.164)	(0.137)	(0.610)
$ExShock$	-0.453	-0.294	-0.964*	-0.576	-0.374	-1.194**
	(0.535)	(0.538)	(0.585)	(0.508)	(0.463)	(0.554)
Region×Year	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y	Y
N	673	673	673	673	673	673

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Change in Mortality Rate of Children aged 1-4 and Shocks: 2SLS

	SO2		TSP		NO2	
Dep. Var: ΔMR_{1-4}	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^p$	0.037***	0.036***	0.028***	0.027***	0.132***	0.129***
	(0.010)	(0.010)	(0.007)	(0.006)	(0.033)	(0.033)
$ExShock$	-0.110***	-0.110***	-0.096***	-0.095***	-0.137***	-0.135***
	(0.032)	(0.031)	(0.032)	(0.031)	(0.035)	(0.034)
Region×Year	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^p \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR_{t-1}^2		Y		Y		Y
N	673	673	673	673	673	673

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Change in Infant Mortality Rate and Shocks: SO2 Robustness

Dep. Var: ΔIMR	Energy Production (1)	Import Shocks (2)	High-skill Shock (3)	Share of Ownership (4)	TCZ (5)
$PollExShock^{SO2}$	0.502***	1.101***	0.483***	0.466***	0.502***
	(0.127)	(0.326)	(0.134)	(0.138)	(0.149)
$ExShock$	-1.947***	-1.072*	3.854**	-1.941***	-0.397
	(0.458)	(0.580)	(1.563)	(0.435)	(0.586)
$\Delta EnergyProd$	0.279**				
	(0.130)				
$PollImShock^{SO2}$		-0.467***			
		(0.167)			
$HighSkillShock$			-9.239***		
			(3.427)		
$\Delta Share\ SOE$				7.071**	
				(3.426)	
$\Delta Share\ Foreign$				0.230	
				(3.422)	
TCZ					2.678***
					(0.764)
Region×Year	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y
N	340	673	673	340	673

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.11

A Data Appendix

A.1 Administration Division: Consistent Prefectures

Each prefecture is assigned a four-digit code in the censuses. The codes can change over years, usually due to the urbanization of the rural prefectures ("Diqu") to urban prefectures ("Shi"), which does not necessarily mean re-demarcation. The changing boundary of prefectures is a threat to the consistency of our defined local economies over time. To cope with the problem, we construct a concordance mapping the counties in 1990, 2000 and 2010 to the prefectures where they belong in 2005. By construction, we have consistent 340 prefectures over years. The municipalities Beijing, Chongqing, Shanghai and Tianjin are treated as prefectures in this paper.

A.2 Industrial Classifications

Our dataset is complied from multiple sources which adopt different industrial classifications. We map the data on employment share, emission intensities, exports, tariffs, and so on to consistent 3-digit CSIC codes. The details are provided as follows. (1) CSIC employed by our data sources has three versions, CSIC1984, CSIC1994 and CISC2002. We firstly build the concordances which map 4-digit CSIC codes of different versions to consistent 3-digit CSIC codes. (2) To convert the ISIC data to CSIC, we employ the concordance built by Dean and Lovely (2010) which cross-matches the four-digit CSIC2002 and ISIC Rev.3. (3) For the SIC data, we firstly concord it to ISIC Rev.3 using the concordance provided by the United Nations Statistics Division, and then map it to CSIC2002.

A.3 Relative Employment Ratio Employed in Figure 1

To construct the employment ratio employed in Figure 1, we first group industries into $Clean$ (C) and $Dirty$ (D) groups, according to whether the sectoral value of SO_2 emission intensity is above or below the median. The clean industry group has an average SO_2 emission intensity of 1.46 pounds per thousand dollar value output. In contrast, the emission intensity for dirty group is 16.2 pounds per thousand dollar value output. Then, we group industries into $HighShock$ (H), $MediumShock$ (M) and $LowShock$ (L) groups, according to whether the industry lies in the upper, middle or bottom tertile of dollar export growth per worker during the period 2000-10. We find that $HighShock$ industries experienced export shock of 168.1 dollars per worker on average. The corresponding values of $MediumShock$ and $LowShock$ groups are 17.35 and 3.77, respectively. Using the 2000 census data, for each prefecture, we calculate its employment in industries that are $Clean$ and experienced $HighShock$ ($EmpShare(CH)$), and similarly values for $EmpShare(DH)$,

$EmpShare(CL)$ and $EmpShare(DL)$. Then, we construct the relative employment ratio of high-export-growth industries as follows:

$$\frac{EmpShare_i(DH)}{EmpShare_i(CH) + EmpShare_i(DH)}\ .$$

Analogously, the relative employment ratio of low-export-growth industries is:

$$\frac{EmpShare_i(DL)}{EmpShare_i(CL) + EmpShare_i(DL)}\ .$$

A.4 Prefecture Level Data on Wind Direction

The data on wind direction is collected from NOAA Integrated Surface Global Hourly Data. We collapse the hourly data to the daily level and calculate the average wind direction for each weather station-day observation using the "unit-vector" average method according to NOAA.[42] The wind direction is categorized into 37 groups, i.e., $wd \in \{0, \frac{\pi}{36}, ..., \frac{35\pi}{36}, No\ Wind\}$. We drop the weather stations with more than 40% of the daily observations within a decade are missing. There are 544 and 394 weather stations in our samples for the decade 1990-2000 and 2000-2010, respectively.

We impute the data on wind direction to each prefecture using the data from its nearest weather station.[43] For each prefecture, we calculate the share of days that the wind direction is wd for each decade, i.e., 1990-2000 and 2000-2010. It is denoted by $s_{it,wd}$.

A.5 Employment Weighted and Wind Direction Weighted Neighboring Export Pollution Shocks

We identify the set of prefectures sharing a border with each prefecture i, and denote it by $Neighbor_i$. The employment weighted neighboring pollution shock is defined as follows:

$$PollutionExportShock_{i,t}^{p,N} = \sum_{r \in Neighbor_i} \psi_{irt} PollutionExportShock_{rt}^{p}\ ,$$

where $\psi_{irt} = \frac{L_{rt-1}}{\sum_{r' \in Neighbor_i} L_{r't-1}}$ denotes the employment weight of prefecture r among all the neighboring prefectures of i.

The wind direction weighted neighboring export pollution shock is constructed as follows

[42] More details can be found in http://www.ndbc.noaa.gov/wndav.shtml.

[43] The nearest weather station is identified as the one with the shortest distance to the centroid of a prefecture. As is discussed in the Section 7, we test the robustness of the result using the data from the first and second most nearest weather stations.

$$WindPollutionExportShock_{i,t}^{p,N} = \sum_{wd \in \{0, \frac{\pi}{36}, \ldots, \frac{35\pi}{36}, NW\}} \sum_{r \in Neighbor_i} \pi_{irt,wd} PollultionExportShock_{rt}^{p} \,.$$

The neighboring prefecture r's export pollution shock is weighted by

$$\pi_{irt,wd} = \frac{s_{rt,wd} w_{ir,wd}}{\sum_{wd} \sum_{r} s_{rt,wd} w_{ir,wd}} \,,$$

where $s_{rt,wd}$ denotes the share of days in which the wind direction is wd in neighboring prefecture r and decade t. $w_{ir,wd}$ captures the weight of different wind directions. It is determined by the relative position between i and r and the wind direction in r, and it is constructed as follows:

$$w_{ir,wd} = \begin{cases} \frac{1}{2}[1 + \cos(\theta_{ir,wd})] & \text{if} \quad wd \in \{0, \frac{\pi}{36}, \ldots, \frac{35\pi}{36}\} \\ 0 \quad \text{if} \quad wd = No\,Wind \end{cases} \,,$$

where $\theta_{ir,wd}$ denotes the *absolute value* of the angle between neighboring prefecture r's angular position and its wind direction wd. The example in Figure A.3 illustrates how $\theta_{ir,wd}$ is calculated. The green triangle represents a prefecture, who has three neighboring prefectures (r = 1,2 and 3) represented by blue circles. The neighboring prefectures are located in the Northwest, South and East. (Their angular position to i are $3\pi/4$, $3\pi/2$ and 0, respectively.) Suppose the wind directions in the three neighboring prefectures are $\pi/4$, 0 and $\pi/3$, respectively. Then the angles between their angular position and wind direction are $\theta_{1,\pi/4} = \pi/2$, $\theta_{2,0} = \pi/2$ and $\theta_{3,\pi/3} = \pi/3$, respectively. Note that $w_{ir,wd} = 1$ if prefecture i is in the downwind position of r, i.e., $\theta_{ir,wd} = 0$, and $w_{ir,wd} = 0$ if prefecture i is in the upwind position of r, i.e., $\theta_{ir,wd} = \pi$. This weighting scheme is intuitive. Prefecture i receives more cross-border pollution from prefecture r if i is located downwind of r more often, i.e., $s_{rt,wd} w_{ir,wd}$ is larger.

A.6 Input-Output Tables

To construct the alternative export shocks as described in section 6.2.1, we use the 1997 and 2007 input-output (IO) tables published by National Bureau of Statistics China. The 1997 IO table contains information of input-output relationships among 124 industries, 70 of which belong to manufacturing sector. The 2007 IO table contains information of input-output relationships among 135 industries, 80 of which belong to manufacturing sector. We aggregate and match our trade, employment and pollution intensity data to the industries in the IO tables.

B Quality Assessment of the Chinese Data Pollution and Mortality

In this section, we address the concern that official reports from the Chinese government may not be fully reliable due to the desire to misreport pollution and mortality.

B.1 Data Quality of Air Pollution: Comparison of Official Data and US Embassy Data

Since 2009, the US Embassy started to monitor and report the hourly concentration of $PM2.5$, the particulate matters up to 2.5 micrometers in size, in five major cities in China, i.e., Beijing, Chengdu, Guangzhou, Shanghai and Shenyang. The data are collected independently of Chinese government agencies, and hence provide a benchmark to check the validity of the official pollution data. As discussed earlier, environmental protection was unlikely to be a major factor determining a politician's career trajectory in the past, so if the manipulation of the official pollution data existed, it is more likely to have occurred in the later period. Therefore, we believe the comparison is informative, although it is restricted to the later years.

Daily Average of Air Quality Index (AQI)

MEP publishes AQI and the main pollutant daily for major cities in China. According to MEP, the AQI and the main pollutant are derived following the steps: (1) convert the pollution readings to $IAQI^p$ for each pollution p; (2) construct the overall AQI using the formula $AQI = max\{IAQI^1, IAQI^2, ..., IAQI^P\}$; (3) the main pollutant is p if $IAQI^p = max\{IAQI^1, IAQI^2, ..., IAQI^P\}$. The information of individual pollutant index $IAQI^p$ is not public available. However, we know that $AQI = IAQI^{PM2.5}$ conditional on the main pollutant being $PM2.5$.

We obtain the daily data from MEP for 2014. The hourly data from US Embassy is aggregated to daily data, and converted to $IAQI^{PM2.5}$ using the conversion table provided by MEP. The summary statistics of the two data series are presented in Table A.1. We find that, conditional on that the main pollutant being PM2.5, the correlation of the two series is very high, ranging from 0.94 for Chengdu to 0.97 for Shanghai. The average $IAQI^{PM2.5}$ of MEP data is generally lower than the US embassy data, with largest discrepancy observed for Beijing. The discrepancy is likely be due to the different locations where the data is collected. In each city, the US embassy readings are collected from only one monitor located in a populous area, while the MEP readings are collected from multiple locations including suburban areas.

Annual Average of *PM2.5* (*PM10*) Concentration

The cities in China started to monitor $PM2.5$ in 2013. Until then, only the concentration level of $PM10$, the particulate matters up to 10 micrometers in size, was reported. As the $PM2.5$ belongs to the $PM10$, the concentration level of the former should should always be smaller than the latter. It is taken as strong evidence for data manipulation if we detect the concentration level of $PM10$ reported by MEP is smaller than that of $PM2.5$ reported by US Embassy. As is shown in Table A.2, the official data of $PM2.5$ track the US Embassy data closely in 2013. In addition, we fail to find any case such that the concentration level of $PM10$ reported by MEP is smaller than that of $PM2.5$ reported by US Embassy.

B.2 Data Quality of IMR: Comparison of Cohort Size across Censuses

Infant mortality rate is measured with error if either number of births or number of deaths is misreported. One may concern that due to the One Child Policy, households may have incentives to underreport live births or over-report infant mortality to hide unsanctioned births. To investigate this possibility, we compare the population size of a newborn cohort across census years. In particular, we predict the cohort size of Age 0 ten years later, $Pop_{0,i,t+10}$, using the information of mortality rate of age groups of 1-4 and 5-10, as follows

$$Pop_{0,i,t+10} \approx (B_{i,t} - D_{0,i,t})(1 - \frac{D_{1-4,i,t}}{Pop_{1-4,i,t}})^4(1 - \frac{D_{5-10,i,t}}{Pop_{t-10,i,t}})^5 ,$$

where $B_{i,t}$ is the number of births of prefecture i in census year t, $D_{a,i,t}$ and $Pop_{a,i,t}$ denote respectively the number of deaths and population of age group a in prefecture i and census year t. In principle, without inter-region migration, the predicted population size of Age 10 in census year t+10, $Pop_{0,i,t+10}$, should closely track the actual population size if the data on number of births and deaths are free of measurement error. However, if either $B_{i,t}$ is prevalently underreported (over-reported) or $D_{0,i,t}$ is over-reported (underreported), one should expect the predicted population size of Age 10 to be always smaller (larger) than the actual data.[44]

Figure A.2 plots the log of predicted Age 10 population $Pop_{0,i,2000+10}$ (derived from the 2000 census), against the log of actual Age 10 population $Pop_{10,i,2010}$ (obtained from the 2010 census).[45] The points are closely cluster along the 45 degree line, suggesting the birth and death statistics are not systematically misreported. The coefficient of correlation between the predicted and actual log Age 10 population is as high as 0.984. In addition, we find that the prefectures that lies significantly below the 45 degree line are the ones receiving large net inflows of immigrants. As a

[44] As it is more difficult to hide a ten-year-old than an infant, we consider that the actual population size of Age 10 in census year $t + 10$ is subject to less misreporting.

[45] The findings are similar when comparing the 1990 and 2000 censuses (available on request).

result, the actual population size is larger than the predicted population size.

C Employment Share and Export Share

In this section, we use data in 2000 and investigate the correlation between a prefecture's share in national export export and its employment share. Specifically, we estimate the following regression[46]

$$\frac{X_{iRk}}{X_{CRk}} = \alpha \frac{L_{ik}}{L_{Ck}} + \varepsilon_{ik} \ .$$

The estimated coefficient of α is 0.965 with robust standard error 0.046. The null hypothesis $H_0: \ \alpha = 1$ cannot be rejected. As is discussed below, when $\alpha = 1$ and under certain conditions, the discrepancy between the export share and the employment share only leads to classical measurement error and results in attenuation bias.

Consider the following (simplified) model:

$$y_i = \beta_0 + \beta_1 x_i + u_i \ ,$$

where $x_i = \sum_k \pi_{ik} \Delta X_{CRk}$ and $\pi_{ik} = X_{iRk}/X_{CRk}$. Due to the data limitation, we cannot observe π_{ik} directly and use $\tilde{\pi}_{ik} = L_{ik}/L_{Ck}$ as a proxy instead. We have established that, from the data, $\pi_{ik} = \tilde{\pi}_{ik} + \varepsilon_{ik}$. Hence,

$$y_i = \beta_0 + \beta_1 \tilde{x}_i + (u_i + \beta_1 e_i) \ ,$$

$$\text{where} \quad \tilde{x}_i = \sum_k \tilde{\pi}_{ik} \Delta X_{CRk} = \underbrace{\sum_k \pi_{ik} \Delta X_{CRk}}_{x_i} - \underbrace{\sum_k \varepsilon_{ik} \Delta X_{CRk}}_{e_i} = x_i - e_i \ .$$

In the following discussion, we make a simplifying assumption that

$$\lim_{N\to\infty} \frac{1}{N} \sum_i u_i e_i = \lim_{N\to\infty} \frac{1}{N} \sum_k \Delta X_{CRk} \sum_i \varepsilon_{ik} u_i = 0 \ ,$$

i.e., in the limit the measurement error is uncorrelated with the other unobserved determinants. Then, it is straightforward to show that the approximation of X_{iRk}/X_{CRk} by L_{ik}/L_{Ck} only leads to classical measurement error if

$$\lim_{N\to\infty} \frac{1}{N} \sum_i x_i e_i = \lim_{N\to\infty} \frac{1}{N} \sum_i \big(\sum_k \pi_{ik} \Delta X_{CRk} \sum_k \varepsilon_{ik} \Delta X_{CRk} \big) = 0 \ .$$

[46] The export share is derived from 2000 data of the Chinese Industrial Annual Survey. Note that the survey does not cover private firms with annual revenue below 5 million RMB. As a result, the data on export share are also subject to measurement errors.

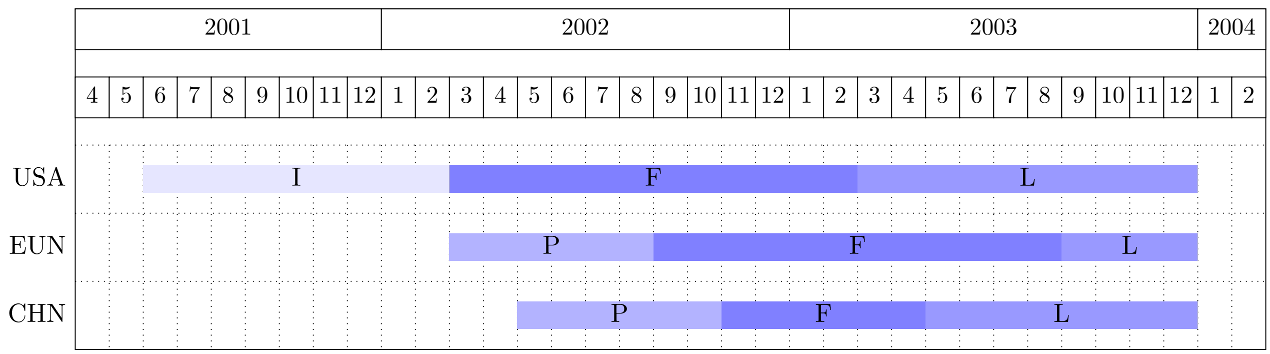
A sufficient condition for $\lim_{N\to\infty}\frac{1}{N}(\sum_i x_i e_i) = 0$ is $\lim_{N\to\infty}\frac{1}{N}\sum_i \pi_{i,k}\varepsilon_{i,k'} = 0 \ \forall k, k'$. That is, in the limit the measurement error is uncorrelated with a prefecture's export composition.

D Additional Results

D.1 Robustness Checks: Effect of Export Shocks on Changes in $PM2.5$ Concentration

In this section, we present a variety of robustness tests on the effect of export expansion on changes in pollutant concentration. We focus on pollutant $PM2.5$ because, due to the data limitation, some of our robustness checks are restricted to the second decade (2000-10) for which we have more observations for $PM2.5$ concentration. The results appear in Table A.7. Column (1) include $WindPollutionExportShock^{TSP,N}$ as an additional control. Albeit less precisely estimated, we find neighboring pollution export shock has a positive effect on $PM2.5$ concentration. More importantly, the estimated coefficient of $PollutionExportShock^{TSP}$ remains similar to our baseline findings in Table 5, which again suggest that local pollution export shock affects $PM2.5$ concentration independent of cross-border spillovers. Columns (2)-(6) repeat the regressions in Table 13. We find that our results are robust to the inclusion of fossil energy production, although the expansion in energy production increases local $PM2.5$ concentration. The estimated coefficient of $PollutionExportShock^{TSP}$ is also robust to the considerations of pollution import shock, export-induced skill demand shock, changes in the ownership structure and TCZ policy. Moreover, as shown in columns (7) and (8) we find consistent results when we take into account of the input-output linkage or use output shocks as alternative measures.

Figure A.1: Timeline of Steel Safeguard



Note: I-Investigation; P-Provisional Measures; F-Final Measures; L-First Scheduled Liberalization.

Figure A.2: Predicted and Actual Population Size of Age 10 in 2010

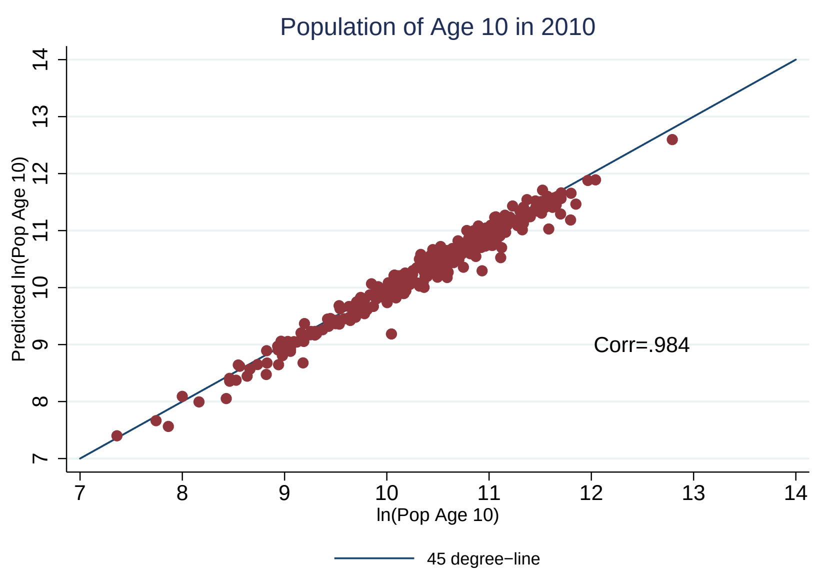


Figure A.3: Wind Direction Example

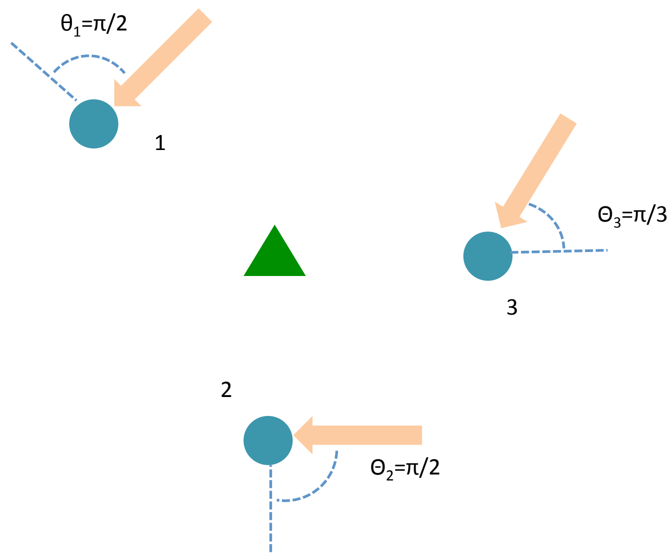


Table A.1: Correlation of pollution data of US embassy and MEP (AQI)

	Conditional on Main Pollutant is $PM2.5$				Unconditional
City	US Embassy	MEP	Corr.	$PM2.5\%$ days	Corr.
Beijing	214.995	168.109	0.956	47.945	0.932
	(9.084)	(5.955)			
Shanghai	105.092	104.453	0.972	37.534	0.916
	(3.774)	(3.706)			
Guangzhou	103.248	94.765	0.947	32.603	0.641
	(3.258)	(2.931)			
Chengdu	154.702	140.000	0.938	47.945	0.945
	(5.015)	(5.047)			
Shenyang	174.187	150.550	0.950	38.356	0.941
	(7.154)	(5.057)			

Note: Standard errors in the parentheses. The hourly data for PM2.5 from US Embassy is aggregated to daily average. The daily observations with less than 12 valid readings are dropped.

Table A.2: Concentration of $PM2.5$ ($PM10$) from different sources (mg/m^3, 2013)

	Beijing		Shanghai		Guangzhou		Chengdu	
	US $PM2.5$	MEP $PM2.5$ ($PM10$)	US $PM2.5$	MEP $PM2.5$ ($PM10$)	US $PM2.5$	MEP $PM2.5$ ($PM10$)	US $PM2.5$	MEP $PM2.5$ ($PM10$)
2013	0.102	0.09	0.060	0.062	0.055	0.053	0.098	0.097
		(0.108)		(0.082)		(0.072)		(0.15)
2012	0.090	(0.109)	0.051	(0.071)	0.058	(0.069)		
2011	0.099	(0.113)						
2010	0.104	(0.121)						
2009	0.102	(0.121)						

Note: The hourly data for $PM2.5$ from US Embassy is aggregated to daily average. The daily observations with less than 12 valid readings are dropped. The annual average is calculated based on the daily average data. Chinese Official data comes from Chinese Environmental Yearbooks and the Bulletins published by Bureaus of Environmental Protection. The concentration levels of $PM2.5$ are only available since 2013. The data for $PM10$ in parentheses are included for comparison.

Table A.3: Changes in Infant Mortality Rate and Shocks by Causes of Death: TSP, 2SLS

	Cardio-Respiratory		Infant Specific		Digestive	
Dep. Var: ΔIMR^C	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^{TSP}$	0.313***	0.496**	-0.357	0.356	-0.005	0.009
	(0.107)	(0.199)	(0.385)	(0.631)	(0.019)	(0.064)
$ExShock$		-2.105		-5.099		0.344
		(1.737)		(4.652)		(0.358)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^p \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

	Infectious		External Causes		Malnutrition	
	(7)	(8)	(9)	(10)	(11)	(12)
$PollExShock^{TSP}$	0.086***	0.081	0.110	0.478	-0.019	-0.021
	(0.032)	(0.069)	(0.089)	(0.418)	(0.022)	(0.041)
$ExShock$		-0.693		-2.470		0.038
		(0.541)		(2.489)		(0.197)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^p \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

Notes: All regressions are weighted by total birth. All regressions start of period overall mortality rate, change in log GDP per capita, change in hospital beds per capita, and change in agricultural employment share. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Changes in Infant Mortality Rate and Shocks by Causes of Death: NO2, 2SLS

	Cardio-Respiratory		Infant Specific		Digestive	
Dep. Var: ΔIMR^{C}	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^{NO2}$	1.009***	2.241**	-1.736	-2.471	0.051	-0.038
	(0.360)	(1.002)	(1.408)	(3.739)	(0.083)	(0.266)
$ExShock$		-4.401		0.302		0.408
		(2.782)		(8.104)		(0.496)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^{p} \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

	Infectious		External Causes		Malnutrition	
	(7)	(8)	(9)	(10)	(11)	(12)
$PollExShock^{NO2}$	0.237**	0.459	0.052	1.137	-0.064	-0.168
	(0.103)	(0.395)	(0.286)	(1.266)	(0.072)	(0.216)
$ExShock$		-1.380		-1.781		0.214
		(0.842)		(2.383)		(0.361)
Region	Y	Y	Y	Y	Y	Y
$\sum_k \gamma_{kt}^{p} \frac{L_{ikt-1}}{L_{it-1}}$		Y		Y		Y
N	117	117	117	117	117	117

Notes: All regressions are weighted by total birth. All regressions start of period overall mortality rate, change in log GDP per capita, change in hospital beds per capita, and change in agricultural employment share. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Change in Infant Mortality Rate and Shocks: TSP, Robustness

Dep. Var: ΔIMR	Energy Production (1)	Import Shocks (2)	High-skill Shock (3)	Share of Ownership (4)	TCZ (5)	IO Adjusted Shocks (6)	Output (7)
$PollExShock^{TSP}$	0.261***	0.497***	0.381***	0.216**	0.383***	0.062**	
	(0.100)	(0.145)	(0.105)	(0.093)	(0.107)	(0.026)	
$ExShock$	-1.462***	-0.423	2.496*	-1.434***	-0.325	0.242	
	(0.399)	(0.486)	(1.423)	(0.378)	(0.528)	(0.299)	
$\Delta EnergyProd$	0.307**						
	(0.131)						
$PollImShock^{TSP}$		-0.124					
		(0.107)					
$HighSkillShock$			-6.945**				
			(3.407)				
$\Delta Share\ SOE$				7.182**			
				(3.420)			
$\Delta Share\ Foreign$				0.479			
				(3.506)			
TCZ					2.688***		
					(0.751)		
$PollOutputShock^{TSP}$							0.080***
							(0.027)
$OutputShock$							-0.560**
							(0.258)
Region×Year	Y	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y	Y	Y
N	340	673	673	340	673	673	340

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share and population density. Contemporaneous shocks include change in log GDP per capita, change in share of boys, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share, a dummy of provincial capital city and distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Change in Infant Mortality Rate and Shocks: NO2, Robustness

Dep. Var: ΔIMR	Energy Production (1)	Import Shocks (2)	High-skill Shock (3)	Share of Ownership (4)	TCZ (5)	IO Adjusted Shocks (6)	Output (7)
$PollExShock^{NO2}$	1.908***	2.410***	1.893***	1.719***	2.068***	0.364***	
	(0.458)	(0.681)	(0.509)	(0.437)	(0.480)	(0.113)	
$ExShock$	-2.156***	-1.192*	1.873	-2.096***	-1.089*	-0.074	
	(0.498)	(0.618)	(1.226)	(0.459)	(0.559)	(0.263)	
$\Delta EnergyProd$	0.303**						
	(0.135)						
$PollImShock^{NO2}$		-0.384					
		(0.291)					
$HighSkillShock$			-6.991**				
			(2.831)				
$\Delta Share\ SOE$				6.821**			
				(3.408)			
$\Delta Share\ Foreign$				0.020			
				(3.421)			
TCZ					2.734***		
					(0.766)		
$PollOutputShock^{NO2}$							0.651***
							(0.249)
$OutputShock$							-0.163
							(0.524)
Region×Year	Y	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y	Y	Y
N	340	673	673	340	673	673	340

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Change in $PM2.5$ Concentration and Shocks: Robustness

Dep. Var: $\Delta PM2.5$	Neighboring Shocks (1)	Energy Production (2)	Import Shocks (3)	High-skill Shock (4)	Share of Ownership (5)	TCZ (6)	IO Adjusted Shocks (7)	Output (8)
$PollExShock^{TSP}$	0.178***	0.179***	0.211*	0.184***	0.178***	0.162**	0.033*	
	(0.064)	(0.067)	(0.109)	(0.068)	(0.065)	(0.070)	(0.019)	
$ExShock$	-0.708	-0.585	-0.655	-0.900	-0.613	-0.617	-0.067	
	(0.574)	(0.530)	(0.553)	(1.397)	(0.519)	(0.513)	(0.252)	
$Wind\ PollExShock^{TSP,N}$	0.132							
	(0.128)							
$\Delta EnergyProd$		0.209**						
		(0.092)						
$PollImShock^{TSP}$			-0.042					
			(0.129)					
$HighSkillShock$				0.699				
				(2.690)				
$\Delta Share\ SOE$					0.615			
					(2.701)			
$\Delta Share\ Foreign$					1.131			
					(4.027)			
TCZ						1.516*		
						(0.887)		
$PollOutputShock^{TSP}$								0.043**
								(0.019)
$OutputShock$								-0.120
								(0.259)
Region×Year	Y	Y	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y	Y	Y
Contemporary Shocks	Y	Y	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y	Y	Y
$\sum_k \gamma^p_{kt} \frac{L_{ikt-1}}{L_{it-1}}$	Y	Y	Y	Y	Y	Y	Y	Y
N	340	340	340	340	340	340	340	340

Notes: All regressions are weighted by population of age 0. Initial conditions include start of period GDP per capita, overall mortality rate, agriculture employment share, population density and a dummy of provincial capital city. Contemporaneous shocks include change in log GDP per capita, change in sex ratio of the new born, change in share of population with middle school education, change in share of population with high school education or above, change in number of hospital beds per capita, change in agricultural employment share and an interaction term of distance to the nearest port and decade dummy. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1