Trade, Pollution and Mortality in China

Matilde Bombardini (UBC, CIFAR and NBER),
and Bingjing Li (National University of Singapore)

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Abstract

Did the rapid expansion of Chinese exports between 1990 and 2010 contribute to the country's worsening environmental quality? We exploit variation in local industrial composition to gauge the effect on pollution and health outcomes of export expansion due to the decline in tariffs faced by Chinese exporters. In theory, rising exports can increase pollution and mortality due to increased output, but they may also raise local incomes, which can in turn promote better health and environmental quality. The paper teases out these competing effects by constructing two export shocks at the prefecture level: (i) the pollution content of export expansion; (ii) export expansion in dollars per worker. We find that the pollution content of exports affects pollution and mortality: a one standard deviation increase in the shock increases infant mortality by 4.1 deaths per thousand live births, which is about 23% of the standard deviation of infant mortality change during the period. The dollar value of export expansion reduces mortality by 1.2 deaths, but the effect is not statistically significant. We show that the channel through which exports affect mortality is pollution concentration. 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. Finally, 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.

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1 Introduction

Among the many dimensions of China's economic growth in the last 3 decades is the contemporaneous boom in export performance: the annual export growth rate was 14% during the 1990s and 21% during the 2000s. 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.[1] This paper studies how the export boom in China between 1990 and 2010 affected pollution and infant mortality across different Chinese prefectures. The specific question we tackle is whether areas that were more involved in the export boom witnessed a deterioration or improvement in pollution and health outcomes relative to less exposed areas. This is ex ante unclear as an export boom brings about more production and therefore pollution (the "scale" effect in Copeland and Taylor, 2003), but also higher incomes, which may affect both pollution and health outcomes in the opposite direction.[2]

We capture these potentially opposite channels through two export exposure shocks. For each Chinese prefecture we construct: (i) $PollExShock$, which represents the pollution content of export expansion and is measured in pounds of pollutant per worker; (ii) $ExShock$, which measures the dollars per worker associated with export expansion. The variable $ExShock$ measures the extent to which a prefecture is initially specialized in industries that subsequently experience a large export increase. The variable $PollExShock$ 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 $PollExShock$.

There are two key features of these measures. First, they rely on variation across prefectures in the initial pattern of comparative advantage across industries, similarly to the approach by Edmonds et al. (2010), Topalova (2010), Kovak (2013) and Autor et al. (2013) to study the effects of import competition on employment. The second feature is that, differently from these studies, here we are interested in the effect on China of the *export* demand shock generated by the rest of the world. The paper therefore builds an export expansion measure that captures the portion 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 export and of output growth more in general? In general, production for both domestic consumption and exporting responds to a

[1]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.

[2]Again, in the language of Copeland and Taylor (2003) and Grossman and Krueger (1995), 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.

multitude of shocks. These include the *national-level* supply shocks, 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. The paper therefore focuses on a specific dimension of aggregate demand where this identification problem is alleviated. It makes use of the presence of externally imposed tariffs, thus isolating foreign demand shocks from other unobserved sources of output dynamics.

We employ the shift-share approach instead of actual export expansion, to identify the causal relationship running from tariff-predicted export expansion to local environmental and health outcomes. At the *prefecture level*, there could be numerous supply shifters that simultaneously affect export performance and environmental/health outcomes. For example, a weakening in the enforcement of environmental regulations may increase local exports by reducing production costs, but this may also lead to environmental degradation and worsening health outcomes. By *not* employing export growth at the local level, but rather using a weighted average of national export expansion with the weights determined by the initial industry composition, the shift-share design helps purging such potential confounding factors.

Magnitudes are substantial. We find that a one standard deviation increase in $PollExShock$ increases infant mortality by an additional 4.1 infant deaths per one thousand live births, while a one standard deviation increase in $ExShock$ decreases infant mortality by a statistically insignificant 1.2 infant deaths.[3] The size of these effects has to be gauged in the context of the evolution of infant mortality over this period. In our data, 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 deaths. The effect of $ExShock$ not only is insignificant, but is only equivalent to 6.6% of such standard deviation.

In two different exercises we calculate the overall effect of the two shocks and illustrate that both at the national level and at the provincial level export expansion had primarily a negative effect, i.e. very few prefectures had a net improvement in health outcomes. Ignoring a potentially beneficial effect of trade common to all prefectures that our cross-prefecture approach necessarily nets out, we calculate that an extra 803,088 infant deaths during the 1990-2010 period are due to export expansion. Importantly, using the same data as Chen et al. (2013), we can show that the negative effects of trade on health are concentrated in mortality due to cardio-respiratory conditions, which are the most sensitive to air pollution, corroborating our findings.

How do $PollExShock$ and $ExShock$ affect mortality? The next question we tackle is the quantification of the channels through which these two shocks influence health outcomes. The

[3]We find that $ExShock$ 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).

most intuitive way in which *PollExShock* affects mortality is through pollutant concentration. Instead *ExShock* may affect mortality through different channels.[4] Our identification relies on the assumption that conditional on *ExShock*, *PollExShock* affects mortality only through the channel of air pollution. We show that a positive *PollExShock* increases the concentration of SO_2, while *ExShock* tends to reduce it. In the decade 2000-2010 a one standard deviation increase in *PollExShock* increases SO_2 concentration by 6.3 $\mu g/m^3$ while a one standard deviation increase in *ExShock* decreases SO_2 concentration by 2.1 $\mu g/m^3$ (this latter effect is not statistically significant). These changes represent respectively 19% and -6.3% of the standard deviation of SO_2 concentration change during 2000-2010.[5] We have two possible 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 local increases in income may not directly translate into local changes in policy.[6] 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, the paper shows how pollution affects infant mortality, a link which has been studied in the previous literature, but for which we offer a novel identification strategy. We find the elasticity of infant mortality to SO_2 to be 0.81. This 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 $PM_{2.5}$ is 1.9.[7]

We are careful in addressing a series of issues that may affect confidence in these results. Importantly, like all studies employing a shift-share approach, our paper faces the challenge of establishing that the results are not simply due to the initial pattern of industrial specialization. It is plausible for example to hypothesize that prefectures initially specialized in dirty industries would experience a relative increase in mortality over this period even without export shocks. This issue is at the heart of Goldsmith-Pinkham et al. (2018), who emphasize how, with Bartik-style variables, identification relies on the exogeneity of the initial industry shares. We calculate Rotemberg weights as proposed by Goldsmith-Pinkham et al. (2018) in Appendix F.2, and show that: i) they are less concentrated in a few industries relative to Autor et al. (2013) and ii) there are no pre-trends in infant mortality associated with the employment share of high Rotemberg weights

[4]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.

[5]We also find that $PM_{2.5}$ concentration induced by a standard deviation increase in *PollExShock* is $\mu g/m^3$, which amounts to 17.7% of the standard deviation of the decadal change in $PM_{2.5}$ concentration. The corresponding numbers for a standard deviation increase in *ExShock* are -1.6 $\mu g/m^3$ (not statistically significant) and 16.8%, respectively.

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

[7]This 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.

industries. We also perform the "balance" checks proposed under the alternative identification assumptions discussed by Borusyak et al. (2018) and show that at the industry level, pollution embodied in exports is uncorrelated with industry-specific weighted average of other local shocks such as changes in educational attainment, health expenditure proxies etc. Aside from these formal checks, in the paper we also control for pre-existing trends and present placebo tests as customary in this literature.

Because concerns about initial industrial specialization are so important for the identification and quantification at the core of this paper, in what follows we present a graphical exercise that serves two purposes. First, it addresses in an intuitive way the key concern that having a high employment share in a dirty industry is entirely responsible for the subsequent increase in infant mortality, regardless of trade shocks. Second, it illustrates the basic nature of the exercise, which is analogous to a continuous difference-in-differences as clarified by Goldsmith-Pinkham et al. (2018). Simply having high employment shares in dirty industries is not enough to predict a high increase in mortality. A prefecture must have a high employment share in an industry that has *both* high emission intensity and high trade exposure. 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).[8] 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:

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

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.

The paper reports a number of other checks to probe our results. For example, we 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 five Chinese cities. We show that the correlation is above

[8] 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) tercile of export growth per worker. More details can be found in Appendix C.

94 percent. 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.[9] Finally, 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.

1.1 Relation to the Literature

Our study contributes to three main strands of the literature, the one related to trade and pollution, the one studying the effect of pollution on mortality and finally, the broader area exploring the effect of international trade at the local level. 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. 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

[9] The results of this event study is reported in Appendix A.

general equilibrium effects and therefore we will not be able to conclusively say whether China as a whole saw its environmental quality improve or worsen because of trade expansion.

In a recent contribution Shapiro and Walker (2018) conclude that trade has not played a quantitatively significant role in explaining the large decline in emissions in the US between 1990 and 2008. Detailed plant-level data allows them to pin most of the change in emissions on within-plant changes in techniques of production. Other recent contributions have focused on the firm-level link between exporting and emissions. In the cross-section Forslid et al. (2018) find that exporters tend to have lower emission intensities, while Cherniwchan (2017) finds lower emissions as firms are exposed to tariffs cuts in the output market. Interestingly, Barrows and Ollivier (2018) 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.

Our paper also relates 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 (McCaig, 2011).

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. de Sousa et al. (2015) exploit city-level variation in exports and find that increased processing trade in China leads to lower pollution. They focus more on the role of the international segmentation of production, and they do not consider the consequences of trade for infant mortality. In the energy and environmental science literature, 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; Jiang et al. (2015) use atmospheric and air quality models to compute the pollution content of China's exports and an epidemiological model to estimate its effect on mortality in different provinces, whereas we adopt econometric techniques to identify the causal effects of export demand shocks with finer data. Another related literature explores the association between China's economic development and environmental/health outcomes (e.g., Grigoriou et al. (2005), Ebenstein et al. (2015), Zheng and Kahn (2017)). We complement these studies by focusing on export expansion, an important driver of China's economic growth, and on identifying the causal linkages.[10]

This paper also connects the rapidly growing literature that employs the variation in initial regional differences in industry composition to study the differential effects of trade on local economies within a country. One strand of work focuses on import competition, including Edmonds et al. (2010), Topalova (2010), Autor et al. (2013), Kovak (2013), Acemoglu et al. (2016), Kovak and Dix-Carneiro (2017), among others. The other strand of this literature investigates the effects of export opportunities on various outcomes, including child labor (Edmonds and Pavcnik, 2005), labor market adjustment (Brambilla et al., 2012), poverty reduction (McCaig, 2011), and employment (Feenstra et al., 2019). Recent work by Erten and Leight (2019) and Facchini et al. (2019) finds that export expansion due to the reduction in trade policy uncertainty has a substantial impact on China's labor market. Aligned with these studies, our paper studies export demand shocks, but focuses on its effects on environmental and health outcomes. Importantly, we propose a new formulation of the Bartik-style instrument to separately identify the export-induced pollution effect and income effect.

The rest of the paper proceeds as follows. Section 2 describes the various data sources, while Section 2.5 probes the quality of specific variables, like air quality and mortality. In Section 3 we construct our export shock measures and present our identification strategy in two parts: i) we first show the reduced form effect of $PollExShock$ and $ExShock$ on mortality; ii) we then show that export shocks affect mortality through pollution. Section 4 discusses our main results and reports a number of robustness checks. We conclude in Section 5.

2 Data

This section describes the main sources of data for exports, tariffs, mortality, emission intensity and pollution. Additional variables are described in Appendix C.

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 have 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

[10] There is also an extensive body of work on the effects of pollution on health in China's context, including Chen et al. (2013), Tanaka (2015), He et al. (2016), among others. In section 4.4, we will revisit this literature when we compare our estimated effect of air pollution on IMR with the findings in the existing literature.

2000. The information on industry employment structure by prefecture is from the 1% sample of the 1990 and 2000 China Population Censuses. Census data contain relevant information regarding the prefecture of residence and the industry of employment at 3-digit Chinese Standard Industrial Classification (CSIC) level.[11]

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 code level for the years 1992, 2000 and 2010.[12] Data on export tariffs faced by Chinese exporters by destination countries and 4-digit ISIC Rev.3 industries are from the TRAINS Database.[13] We construct the industry-level tariff rates faced by Chinese exporters, which is the weighted average of tariffs imposed in different destination markets:

$$ExTariff_{kt} = \sum_j \frac{X_{jk,t-1}}{X_{k,t-1}} \tau_{jkt} \; .$$

Here, τ_{kjt} denotes the tariff imposed by country j on good k during the period t. The weights are determined by the country's share in China's total exports of good k in the lag period, and they are constructed using the trade flow data from three years earlier. As is shown in Table A.2, on average $\ln(1+ExTariff)$ drops from 0.071 by 0.02 log point over the period 1992-2000. The corresponding numbers for 2000-2010 are 0.051 and 0.015. More importantly, there is substantial variation in tariff cuts. The standard deviations are 0.047 and 0.032 for the two decades, respectively. We map trade and tariff data to the 3-digit CSIC sectoral employment data from the population censuses, using a concordance between ISIC and CSIC.

2.3 Pollution Data

2.3.1 Industry Pollution Intensity

We construct pollution intensity for each 3-digit CSIC industry, using data from the World Bank's Industrial Pollution Projection System (IPPS) and China's environment yearbooks published by the Ministry of Environmental Protection (MEP). The IPPS is a list of emission intensities, i.e., emission per dollar value of output, of a wide variety of pollutants by 4-digit SIC industry. These data were assembled by the World Bank using the 1987 data from the US EPA emissions database and manufacturing census.[14] We aggregate the data to the 3-digit CSIC level and consider the pollutants sulfur dioxide (SO_2), total suspended particles (TSP) and nitrogen dioxide (NO_2) in

[11]The 1990 Census employs CSIC 1984 version and the 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.

[12]1992 is the first year when the export data is available for China at 4-digit ISIC level.

[13]We collect both applied and MFN tariffs.

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

the analysis. To address the concern that China's industrial 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. Therefore, while the level of industry pollution intensity is aligned with the MEP data, the within sector heterogeneity retains features of the IPPS data. See Appendix C.3 for details.

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.[15] 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, we compile an unbalanced panel which covers 203 prefectures.

Satellite information on $PM_{2.5}$ comes from NASA.[16] 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 $PM_{2.5}$ concentration at the prefecture level. [17]

2.4 Mortality Data

Infant mortality rates (IMR) are constructed from the China Population Censuses for years 1982, 1990, 2000 and 2010. Each census records the number of births and deaths within a household during the last 12 months before the census was taken (details in Appendix C.4). The total number of deaths at age 0 is collected for every county, and then aggregated 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 live births. In addition to IMR, we assemble data on the mortality rate of young children aged 1-4 at the prefecture level for the years 1990, 2000 and 2010.[18]

We supplement the census mortality data with vital statistics obtained from the China's Disease Surveillance Points (DSP) system for years 1992 and 2000. The DSP collects birth and death

[15]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 1992 and 2000, however, it was replaced by PM_{10} in 2010.

[16]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.

[17]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.

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

registration for 145 nationally representative sites, covering approximately 1% of the national population.[19] The data recorded whether or not an infant died within a calendar year and the cause of death, using International Classification of Disease 9th Revision (ICD-9) codes.

2.5 Quality Assessment of the Chinese Data on Pollution and Mortality

In this section we address the concern that official reports from the Chinese government may not be 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 ambitious 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 Appendix D 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 D 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 Empirical Specification

In this section we lay out the empirical methodology and explain our identification strategy. Figure 2 illustrates schematically the causality links that this paper explores. "Export" tariffs, i.e., tariffs that Chinese exporters face, affect the extent of export expansion and the pollution embodied,

[19]The surveillance sites are primarily at the county level. We match the surveillance sites to 118 prefectures where they are located.

measured by $ExShock$ and $PollExShock$, which ultimately affect mortality, through pollution concentration. We delve into the measures and mechanism further below.

3.1 Pollution Export Shock and Export Shock

In this section we build empirical measures that capture exports shocks based on the derivation in Appendix B. We expect increased exports to affect pollution through two potential channels, which we capture with two types of export shocks.

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

ii) $ExShock_{it}$ - 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 Appendix B, we believe it must be accounted for in the empirical analysis.

We focus more on channel i) first. As detailed in Appendix B, in what follows we assume that increased exports due to higher demand in the rest of the world were produced by labor primarily moving from rural to urban areas and that was previously employed in subsistence agriculture, rather than industrial production for the domestic market. Conditional on data availability for prefecture-level exports across all years in the sample, we could find the impact of export expansion on local pollution change using the following equation:

$$\Delta C_{it}^{p} = \sum_{k} \gamma_{kt}^{p} \frac{\Delta X_{ikt}}{L_i} \ , \tag{1}$$

where ΔC_{it}^{p} measures the change in concentration of pollutant p in prefecture i between year $t-1$ and year t, γ_{kt}^{p} is the pollution intensity for pollutant p,[20] ΔX_{ikt} is the analogous change in export value from prefecture i in sector k, and L_i denotes the size of prefecture i. Without this normalization by prefecture size, the following example would pose a problem. Imagine that two unequally-sized prefectures face the same total increase in emissions. If we did not normalize by prefecture size, we would attribute the same increase in pollutant concentration to both, whereas the smaller prefecture is in fact facing a larger increase in such concentration. In practice we approximate the size of the prefecture with total employment and note that this normalization does not qualitatively affect our results (see Table 5).

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. Therefore we exploit the model

[20]Specifically, $\gamma_{kt}^{p} = \frac{P_{kt}^{p}}{Y_{kt}}$, where P_{kt}^{p} is the total amount of emissions in sector k and Y_{kt} is the value of output.

prediction in equation (19) to approximate ΔX_{ikt} as $\frac{X_{ik,t-1}}{X_{k,t-1}}\Delta X_{kt}$, where ΔX_{kt} is the change in export from China to the rest of world of industry k in period t. We use employment share $\frac{L_{ik,t-1}}{L_{k,t-1}}$, where $L_{ik,t-1}$ and $L_{k,t-1}$ 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, $\frac{X_{ik,t-1}}{X_{k,t-1}}$. This is, again, because export data at the prefecture level are not available for the earlier time period (1990) of our sample.[21]

In summary, $PollExShock_{it}^{p}$, our empirical measure of export-induced pollution in prefecture i, is constructed as follows:

$$PollExShock_{it}^{p} = \sum_{k} \gamma_{kt}^{p} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{kt}}{L_{k,t-1}} \ , \tag{2}$$

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 $PollExShock_{it}^{p}$ measure easily comparable to our second measure of export shock, which we define simply as $ExShock_{it}$. This second measure, which addresses channel ii), i.e. the impact of export-induced income growth on environmental outcomes, is constructed as follows:

$$ExShock_{it} = \sum_{k} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta X_{kt}}{L_{k,t-1}} \ , \tag{3}$$

and it measures the dollar value of export expansion in prefecture i, on a per worker basis. Importantly the two shocks measure different dimensions of export expansion. While $ExShock_{it}$ measures the total value of all goods being exported, $PollExShock_{it}^{p}$ gives different weights to different sectors according to their emission intensity.

The variable $ExShock_{it}$ 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, $PollExShock_{it}^{p}$ and $ExShock_{it}$ 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 Section 3.2.1.

[21] We adopt different approaches to investigate the potential bias introduced by this approximation. First, in Section 4.3.3, we construct the theoretically consistent measures using the export share data in 2000, and find regression results aligned with the baseline findings. Second, in Appendix E, 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.

3.2 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 trade costs on pollution and mortality across prefectures in China. Our first specification is the following:

$$\Delta IMR_{it} = \alpha_1 PollExShock_{it}^{p} + \alpha_2 ExShock_{it} + \phi_{rt} + \varepsilon_{it} \tag{4}$$

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. The regression stacks the first differences of two periods, 1990 to 2000 and 2000 to 2010. The stacked difference model is similar to a three-period fixed effect model, and removes any time-invariant prefecture-specific determinants of health outcomes. We add to this first-difference specification $Region \times Year$ fixed effects, ϕ_{rt}, to account for differential trends in mortality rate *changes* across 8 macro regions in China (this is comparable, but more demanding than, the Census division fixed effects in Autor et al. (2013)'s stacked first-difference model). In the following section we address issues related to endogeneity.

3.2.1 Identification Strategy

Our basic specification (4) 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 and ethnic composition. Even after the inclusion of such variables, we are still concerned that the error term ε_{it} may be affected by other 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 $PollExShock_{it}^{p}$ and $ExShock_{it}$, 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 prefecture's initial industry composition. As discussed in the introduction, we view this as a the key threat to identification and we address the issue in many ways. The first approach is to control for pre-existing trends in infant mortality, so that we can account for the possibility that a prefecture initially specialized in polluting industries may be on a different trajectory in terms of overall health outcomes. The second approach 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 is to control for the following variable, $PollEmpl$, which measures the level of pollution implied by the initial employment structure in prefecture i:

$$PollEmpl_{it}^{p} = \sum_{k} \gamma_{kt}^{p} \frac{L_{ik,t-1}}{L_{i,t-1}} \; . \tag{5}$$

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 $PollEmpl$ makes sure that we are comparing two prefectures with the same initial average level of specialization in dirty industry, which likely summarizes their attribute 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 a similar value of $PollEmpl$, indicating they have similar initial pollution level. Nevertheless, they may experience different $PollExpShock$, if for example, steel receives a larger external demand shock.

The fourth approach is to more formally calculate the "Rotemberg weights" associated with each industry as suggested by Goldsmith-Pinkham et al. (2018). In Appendix F.2 we show that the Rotemberg weights, which measure the importance of each industry in determining the coefficient of interest and the coefficient's sensitivity to misspecification in each industry share, are less concentrated in a few industries relative to Autor et al. (2013) and that there are no systematic pre-trends in infant mortality associated with the employment shares of industries with high Rotemberg weights.[22]

The fifth approach is to take the complementary view of the identification requirements proposed by Borusyak et al. (2018). In that paper the identification condition is that the industry-level shock is uncorrelated with a weighted average of the unobservable local unobserved shocks, with the weights reflecting the importance of the industry in the local economy. Following this logic, in Appendix F.4 we perform the "balance" test suggested by Borusyak et al. (2018) and show that a weighted average of observable local shocks (e.g. the change in skill level and migrant share) is uncorrelated with $PollExShock$ at the industry level. The test shows that $ExShock$ is instead correlated with some of these averages of local shocks and confirms that we need to control for changes in various socio-economic factors, such as migrant share, skill composition and share of population in agriculture.

Finally, there may be a concern that a high initial employment share in dirty industries may be correlated with the tendency to employ more migrant workers, whose children may systematically have worse health outcomes. Perhaps surprisingly, polluting industries do not systematically employ more migrant workers as a share of their total employment. The first two columns of Table 2 show that pollution intensity is negatively correlated with the share of cross-prefecture

[22] As another robustness check, we implement a related suggestion by Goldsmith-Pinkham et al. (2018) by dropping one 2-digit sector at a time in Table A.8.

migrants in the industry and uncorrelated with the share of workers with rural hukou (a plausible proxy of lower socio-economic status migrants). Given these correlations, the concern that our estimates may be driven by selective migration should be alleviated.

Export Tariffs and Export Shocks

A separate issue from the one related to exogeneity of industry shares is what goes into the national shock that form the Bartik instrument. The typical concern here is that in a finite sample the export expansion at the national level can be driven by a few prefectures which highly specialize in an industry. Goldsmith-Pinkham et al. (2018) suggest a leave-one-out estimator to address this issue, while Autor et al. (2013) employ exports from China to other developed countries to build their Bartik instrument. The second method is preferable if we believe that supply shocks may be correlated geographically. In our context we believe tariffs faced by Chinese exporters can serve this purpose.

A more fundamental reason why we consider tariff-predicted exports is a clean interpretation of the results as the health consequences of foreign demand shocks. We believe changes in the external tariffs to be mainly determined by political considerations in other countries and therefore to be mostly exogenous to China's internal shocks. Nevertheless we need to check that changes in $ExTariff$ are indeed uncorrelated with various shocks within China. In particular, columns (3)-(7) of Table 2 shows that changes in $ExTariff_{kt}$ are uncorrelated with industry-level: (i) changes in domestic demand across different sectors;[23] (ii) changes in value added per worker (as a proxy for productivity growth) across sectors; (iii) emission intensities (i.e., cleaner industries were not being liberalized at a different pace from dirty ones); and (iv) share of migrant workers (i.e., industries that hire more migrant workers did not receive a larger tariff cut). In Figure A.3, we observe that industries with high initial external tariffs tend to receive greater tariff reduction in the subsequent period, and this pattern holds in both decades. The slope of the best fitted line equals -0.52 and is highly significant. This finding implies that the reductions in tariffs faced by Chinese exporters are associated with a protective structure that is set a decade earlier, which also alleviates the concern of the potential endogeneity of tariff cuts.

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:

$$\ln X_{kt} = \theta \ln(1 + ExTariff_{kt}) + \eta_k + \phi_t + \varepsilon_{kt} \ , \tag{6}$$

where η_k and ϕ_t are sector and time fixed effects. We report the results of this regression in Figure 3.[24] The estimated coefficient implies that a 1% increase in the tariff faced by exporters decreases

[23]Domestic demand is constructed as the difference between industry output and exports.

[24]The graph reports applied tariffs, which are highly correlated with MFN tariffs, with a correlation coefficient of 0.98.

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 (6), then take the exponential of such predicted value to obtain $\widehat{X}_{kt}$:

$$\widehat{X}_{kt} = \exp(\hat{\eta}_k + \hat{\phi}_t + \widehat{\theta}\ln(1 + ExTariff_{kt})) \ . \tag{7}$$

We employ predicted exports from (7) in changes, i.e., $\Delta\widehat{X}_{kt}$, to construct instruments for our export shocks of interest. Note that $\Delta\widehat{X}_{kt}$ is the empirical counterpart of dX_{CRk} as in equation (17) implied by the model in Appendix B.

We estimate equation (4) using instrumental variables that are constructed using predicted exports derived in equation (7). The two instrumental variables are constructed as follows:

$$Poll\widehat{ExShock}^p_{it} = \sum_k \gamma^p_{kt} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta\widehat{X}_{CRkt}}{L_{Ck,t-1}} \ , \tag{8}$$

$$\widehat{ExShock}_{it} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta\widehat{X}_{CRkt}}{L_{Ck,t-1}} \ . \tag{9}$$

3.2.2 First Principal Component of Pollution Export Shocks

Since $PollExShock$ across different pollutants are positively correlated, in most of the empirical analysis, we adopt a unified measure, $PollExShock^{PCA}_{it}$, which is the first principal component of the pollution export shocks of SO_2, TSP and NO_2. The corresponding instrument $Poll\widehat{ExShock}^{PCA}_{it}$ is constructed accordingly.[25]

3.3 Specification 2: Pollution Concentration Channel

Our second specification identifies the specific channels through which export shocks affect mortality. In particular we posit that $PollExpShock^p_{it}$ affects mortality only through its effect on pollution concentration while $ExShock_{it}$ 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 2 and are reflected in our choice of specification, which is composed of two equations. The first is the mortality equation, which is similar to (4):

$$\Delta IMR_{it} = \delta_1 \Delta PollConc^p_{it} + \delta_2 ExShock_{it} + \phi_{rt} + \nu_{it} \ , \tag{10}$$

[25] Similarly, we construct $PollEmpl^{PCA}_{it}$, which is the first principle component of the variables for SO_2, TSP and NO_2.

where $\Delta PollConc_{it}^{p}$ 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 $\widehat{PollExShock_{it}^{p}}$ and $\widehat{ExShock}_{it}$ 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 $PollExShock_{it}^{p}$ 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 $\Delta PollConc_{it}^{p}$:

$$\Delta PollConc_{it}^{p} = \rho_1 PollExShock_{it}^{p} + \rho_2 ExShock_{it} + \phi_{rt} + \mu_{it} \tag{11}$$

with the same instruments $\widehat{PollExShock_{it}^{p}}$ and $\widehat{ExShock}_{it}$ employed to identify the causal effects of different export shocks on pollution concentration in a given prefecture.

4 Results

4.1 Summary Statistics

Before delving into the results, we briefly describe the data summarized in Table 1. We focus on the two outcome variables of interest, infant mortality rate (IMR) and pollution concentration, and on the two export shocks of interest, $PollExShock_{it}^{p}$ and $ExShock_{it}$. 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 the 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 decadal 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 of 9 deaths 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 SO_2 of 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,[26] which implies that 75% of Chinese cities did not comply with the recommended threshold in 2000. The data on changes in

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

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. We also detect a similar degree of heterogeneity for $PM_{2,5}$.

Panel C reports the variable $PollExShock_{it}^{p}$ 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 4 show that the variation was not clustered in certain provinces, and that even within provinces different prefectures experienced different levels of $PollExShock$. Panel C also reports a unified measure that we use in most of the empirical analysis, $PollExShock_{it}^{PCA}$, which also displays a large degree of cross-prefecture heterogeneity.

Panel D reports the variable $ExShock_{it}$ as change in exports in 1000 dollars per worker. Notice first that the export shock 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 heterogeneity in 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).

4.2 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, $PollExShock_{it}^{PCA}$ and $ExShock_{it}$ on infant mortality as shown in equation (4). The results appear in Table 3.[27] All columns present instrumental variables regressions as detailed in Section 3.2. (The corresponding results of OLS regressions are reported in Table A.6.) Throughout columns (1) to (8), we control for $Region \times Year$ dummies to account for region specific shocks in different periods that could be correlated with our export shock variables.[28] Following most of the literature on pollution and mortality, we weight observations with population of age 0 at the start of the period. We verify in Table 5 later that our baseline findings are unaffected by this weighting scheme. The standard errors are clustered by province to accommodate the possibility of unobserved correlated shocks

[27] A previous version of this paper employed the three versions of the shock constructed with different pollutants, while here we present most regressions with only the principal component of these shocks, i.e. $PollutionExportShock_{it}^{PCA}$. See Bombardini and Li (2016).

[28] 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).

across prefectures within a given provincial unit.[29]

Column (1) finds a positive and statistically significant effect of $PollExpShock_{it}^{PCA}$. In column (2), we further control for the following variables at the start of the period: log GDP per capita, overall mortality rate, agriculture employment share and population density, and for contemporaneous changes in the following variables: share of male infants, 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 controls of lag change in IMR and its squared term, which addresses the concern that pollution export shock may in part capture prefecture-specific pre-determined trends in IMR. The estimated effect of $PollExShock_{it}^{PCA}$ remains similar. Columns (3) and (4) repeat the analysis, but replace the main variable of interest with $ExShock_{it}$. The effect of export expansion in dollar terms is negative (i.e. infant mortality decreases) as shown in column (3), but becomes statistically insignificant once we introduce all the relevant controls in column (4). Columns (5) and (6) introduces both $PollExShock_{it}^{PCA}$ and $ExShock_{it}$ together. In the full specification (6), the coefficient on $PollExShock_{it}^{PCA}$ remains very similar once we control for $ExShock_{it}$. The coefficient on $ExShock_{it}$ is negative but insignificant. We should note that the correlation between the two variables $PollExShock_{it}^{PCA}$ and $ExShock_{it}$ is 0.74, but this does not seem to result in a collinearity problem.[30] In column (7), in order to further address the concern that prefectures 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., $PollEmpl_{it}^{PCA}$ as described by equation (5). The addition of this variable does not affect our coefficients of interest and confirms that $PollExpShock_{it}^{PCA}$ captures the effect of a focus on dirty industries that *also* experience an export expansion. The associated first stage estimates are reported in Panel B. There is a positive correlation between $PollExShock_{it}^{PCA}$ ($ExShock_{it}$) and its instrument $Poll\widehat{ExSh}ock_{it}^{PCA}$ ($\widehat{ExShock}_{it}$). As suggested by Angrist-Pischke F-statistics, both instruments are strong.

We now comment on the magnitude of these effects. Due to its ability to better account for local changes in unobservable variables, our preferred specification is in column (7). Because the magnitude of export shocks varies by decade, it is worth explaining the resulting effects separately. A one standard deviation increase in $PollExShock_{it}^{PCA}$ in the 1990's brings about 1.67 extra deaths

[29]In Appendix F.5, we follow recommendation of (Borusyak et al., 2018) and investigate the effects of export shocks on IMR at the industry level. This exercise yields similar statistical inference as the prefecture-level regression, which addresses the concern in Adão et al. (2018), namely that the regression error terms could be correlated across prefectures that need not be geographically proximate, yet feature a similar initial industrial structure.

[30]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. In addition, the simulation excercise suggests that despite the high correlation between $PollExShock_{it}^{PCA}$ and $ExShock_{it}$, there is sufficient statistical power to identfiy their independent effects. Simulation details are reported in Appendix F.1.

per thousand births (8.9% of a standard deviation in IMR change over the same period). The equivalent number for the 2000's is 4.89 extra infant deaths per thousand births (33.8% of a standard deviation in IMR change over the same period). Using the statistically insignificant estimate in column (7) to measure the effect of $ExShock$ on mortality, we find that a 1990's standard deviation increase in export per capita causes 0.19 fewer deaths per thousand births, while the equivalent effect for a 2000's standard deviation is 1.59 fewer deaths per thousand live births.[31]

4.3 Robustness Checks

In this section, we demonstrate the robustness of the basic results to many alternative specifications and measures of external demand shocks. The results are reported in Tables 4 to 6.

4.3.1 Future shocks

As discussed in Section 3.2.1, 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. Here we perform a falsification exercise where we regress the current change in IMR on future shocks. More specifically, we stack the first difference of IMR in periods 1982-90 and 1990-2000, and relate them to the export shocks during periods 1990-2000 and 2000-2010, respectively. Table 4 finds no correlation between IMR and future shocks, and moreover the estimated coefficient of $PollExShock$ is much smaller in magnitude. This finding suggests that prefectures hit by larger export shocks were not already experiencing relatively faster increase in mortality rates.

4.3.2 Alternative Fixed Effects and Unweighted Regression

Column (1) of Table 5 replaces Region×Year dummies with Province×Year dummies. This specification identifies the coefficients of interest exploiting variation across prefectures around a province-decade-specific trend, hereby reducing the amount of variation in the export shocks.

[31] By using a weighted average of national export expansion with the weights determined by the initial industry composition, we are able to purge the potential confounding export supply shocks. This Bartik-style approach, however, may ignore the part of the export growth attributable to export-induced industry specialization, because the industry employment shares are fixed at the initial level. Consider the following example. If industry 1 has a higher tariff cut than industry 2, its export will grow more, but region A, initially more specialized in industry 1, may see their export of that good grow more than proportionally relative to region B that is specialized in industry 2. If this is the case, a region that has a large increase as predicted by the shift-share shock actually has an even larger increase. This introduces a multiplicative bias, and the magnitude of the point estimate is overestimated. The importance of this issue is greatly diminshed by assessing the magnitude in terms of standard-deviation-response. Therefore, we adhere to this approach to infer the magnitude of the estimates thoughtout the paper. We also checked that specialization is not a severe concern here, by estimating whether our tariff-induced export growth at the industry level under- or overpredicts actual export change. The OLS coefficient is 0.95 and is not significantly different from 1, indicating that specialization is not a concern in our context.

The coefficient on $PollExShock_{it}^{PCA}$ is somewhat smaller in magnitude, but remains positive and highly significant. Column (2) reports result of the unweighted regression, which resembles the baseline finding. These two specifications find a negative, but not always significant effect of the variable $ExShock_{it}$.

4.3.3 Alternative Measures of External Demand Shocks

Pollution Export Shocks without Normalization. As discussed in Section 3.1, we normalize the total emission induced by export demand shocks by the local total employment because of the consideration that differences in total emissions could be mechanically driven by the size of the prefecture. Although due to this reason we prefer the measure defined in equation (2), we verify here that our results are robust to the alternative measure without the normalization, i.e., $PollExShock_{it}^{p} = \sum_k \gamma_{kt}^{p} \frac{L_{ik,t-1}}{L_{i,t-1}} \Delta X_{kt}$. Column (3) confirms that the normalization does not qualitatively affect the results.

Neighboring Shocks. In column (4), we consider the impact of export shocks experienced by neighboring prefectures. To account for the effects of the wind-born pollution generated by the nearby prefectures, we construct the measure $WindPollExShock_{it}^{PCA,N}$, which is the weighted average of the pollution export shocks of the neighboring prefectures, with the weights determined by wind directions. (The details are provided in Appendix C.8.) To capture the cross-border income spillovers, we further include employment weighted export income shocks of the neighboring prefectures, denoted by $ExShock_{it}^{N}$. We find that an increase in $WindPollExShock_{it}^{PCA,N}$ raises IMR. A neighboring export income shock, on the other hand, tends to reduce IMR. More importantly, the coefficients for local shocks remain similar to those of the baseline regression. This finding suggests that local pollution affects IMR independently of cross-border spillovers. Column (5) consolidates the local and neighboring export shocks, and obtains consistent results.

Input-Output Relation Adjusted Shocks. So far we have not considered how external demand shocks may induce production expansion of intermediate goods, and as a result extra emissions. In particular, our measure may understate the pollution shocks in prefectures specializing in dirty intermediate goods. To alleviate this concern, we use information from China's input-output tables and construct alternative pollution export shock and income export shock as follows:[32]

$$PollExShock_{it}^{p,IO} = \sum_k \gamma_{kt}^{p} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta Y_{kt}}{L_{k,t-1}} , \tag{12}$$

[32]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 C.

$$ExShock_{it}^{IO} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta Y_{kt}}{L_{k,t-1}} \; . \tag{13}$$

ΔY_{kt} is the component of industry k of the vector $(\mathbf{I}-\mathbf{C})^{-1}\mathbf{\Delta X_t}$, where $\mathbf{I}$ is an identity matrix, and $\mathbf{C}$ is the matrix of input-output coefficients and $\mathbf{\Delta X_t}$ is the vector of industry export expansion during the period t. Similar to the baseline analysis, the overall pollution induced by export expansion is captured by the first principal component of the pollution export shocks of SO_2, TSP and NO_2.[33] Aligned with our baseline results, column (6) shows that pollution export shock 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 $PollExShock_{it}^{PCA,IO}$ increases IMR by 3.2 per thousand of live births.

Actual Export Expansion. Due to data limitation we did not use actual prefecture-level exports in our main regressions as this cuts in half the sample. We nevertheless still include this specification as a robustness check. In column (7) we construct both export shocks employing changes in the actual value of exports over the period of 2000-10. More specifically, analogous to equation (1) $PollExShock_{it} = \sum_k \gamma_{kt}^p \frac{\Delta X_{ikt}}{L_{i,t-1}}$, and $ExShock_{it} = \sum_k \frac{\Delta X_{ikt}}{L_{i,t-1}}$, where ΔX_{ikt} represents the change in export of industry k from prefecture i. We maintain the same IV strategy discussed in Section 3.2. The results reported in column (2) align with the baseline findings.[34]

Export Shocks Constructed from Initial Export Shares. We also employ the data on export composition in 2000 to construct both export shocks in the way suggested in Appendix B for the period 2000-2010. More specifically, $PollExShock_{it} = \sum_k \gamma_{kt}^p \frac{X_{ik,t-1}}{X_{k,t-1}} \frac{\Delta X_{kt}}{L_{i,t-1}}$ and $ExShock_{it} = \sum_k \frac{X_{ik,t-1}}{X_{k,t-1}} \frac{\Delta X_{kt}}{L_{i,t-1}}$, where $X_{ik,t-1}/X_{k,t-1}$ captures prefecture i's share in China's export of industry $k$at the start of period. We use the same IV strategy described in Section 3.2, and the results reported in column (8) are consistent with the baseline findings. We take this finding as supporting evidence that our baseline findings are unlikely to be severely biased due to measurement errors introduced by approximating export shares with employment shares.

Export Expansion by Industry Group. In this section we create alternative measures that help understand the two sources of variation that drive our results. More specifically, we hypothesize that export expansion is beneficial to infant mortality only if it happens in clean industries, because the income effect is likely larger than the scale effect in that case. To implement this specification, CSIC industries are ranked according to the pollution intensity of SO2, and the

[33]We also construct the corresponding instruments $\widehat{PollutionExportShock}_{it}^{PCA,IO}$ and $\widehat{ExportShock}_{it}^{p,IO}$ by replacing $\mathbf{\Delta X_{CRt}}$ with tariff-predicted export growth $\mathbf{\Delta \widehat{X}_{CRt}}$. The standard deviation of $PollutionExportShock_{it}^{PCA,IO}$ is 1.705.

[34]An interquartile range increase in pollution export shock induces an increase in IMR by 4.7 per thousand births during 2000-2010.

ones belonging to the bottom and upper halves are classified into Clean and Dirty group, respectively.[35] The measures of local economy's export exposures to different pollution intensity groups are constructed according to

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

where K denotes the sector which industry k belongs to, and $K \in \{Clean, Dirty\}$. By construction, $ExShock_{it}^{K}$ captures the exposure in dollar per worker to export expansion in sector K. We investigate the effects of export shocks of different pollution intensity groups on IMR by estimating the following equation:

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

where $ExShock_{it}^{K}$ are instrumented by $\widehat{ExShock}_{it}^{K}$ that are constructed accordingly. In column (9), we detect a significant effect of dirty export expansion on IMR. It is estimated that a 1000 USD $ExShock^{D}$ increases IMR by 6.5 per thousand births. Moreover, we find a significant effect of clean export expansion on IMR, with a 1000 USD $ExShock^{C}$ reducing IMR by 1.6 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.

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 2000-2010 we have prefecture-level data on output, instead of just exports, so we replace exports with total production and create a *PollOutputShock* and an *OutputShock*, but still adopt the same IV strategy described in Section 3.2. The results in column (10) of Table 5 is in line with the baseline findings.

4.3.4 Additional Controls

Energy Production. The analysis so far has employed, in constructing our *PollExShock*, data that only accounts for the direct emissions generated in the production process, which 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 that may depend on the prefecture where firms are located, regardless of the industry. For our purpose, if electricity generation is not accounted for in our pollution export

[35] Our results are consistent when industries are grouped into terciles, i.e., Clean, Medium and Dirty, and when the industry pollution ranking is based on pollution intensity of other pollutant.

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 present in the prefecture where the export-induced demand for power is arising.[36] In order to address these concerns, we introduce a control at the prefecture level which is the amount of electricity generated by fossil fuel (also measured in dollar value of output per worker). As shown in column (11) of Table 5, the magnitude and significance of $PollExShock$ is not affected, but we find that expansion in energy production, is a significant predictor of increases in infant mortality. We view this result as an indication that the indirect effect of export shocks through energy generation is not very strong, so that once we control directly for fossil fuel generated energy, the coefficient of interest does not change substantially.

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 that the gap between exports and imports has widened.[37] The second reason is that, in principle, increased import 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 caveats, we present a specification where we introduce a $PollImShock$, constructed analogously to our $PollExShock$ by replacing export value with import value. Column (12) of Table 5 finds a significant negative effect of $PollImShock$ on mortality, which provides suggestive evidence for the import substitution channel.

Other Controls. In column (13) we control for a prefecture-level variable $HighSkillShock$, introduced by Li (2018), which measures the extent to which export expansion increases demand for high skill workers.[38] The concern is that $PollExShock$ is capturing expansion in low-skill industries (rather than dirty ones) and that this may be correlated with enforcement of environmental regulations, if prefectures with more educated workers demand higher environmental standards.

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

[37] 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.

[38] 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 $High\widehat{SkillS}hock_{it}$ is constructed by replacing ΔX_{CRkt} by $\Delta \widehat{X}_{CRkt}$.

Although this scenario seems to be confirmed in the data, our coefficient of interest is not affected. In column (14) 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 (15), 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 prefectures where environment deteriorated relatively faster.

4.3.5 Mortality by Gender and Mortality of Young Children Aged 1-4

Table 6 investigates the effects of export expansion on IMR by gender and the effects on mortality of young children aged 1 to 4, using the specification of column (7) 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. Although the difference is not statistically significant, the effect of pollution export shock on girls is 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.

In columns (4)-(6) we follow specification (4), but replace the dependent variable with change in mortality rate (MR) of children aged 1-4. Column (4) shows that one standard deviation increase in $PollExShock$ increases MR of children aged 1-4 by 0.28 deaths per thousand, which is equivalent to 24% of the standard deviation of MR change over this period. Moreover, it is estimated that 1000 USD export expansion reduces MR of age 1-4 by 0.12 per thousand. The coefficients of both $PollExShock$ and $ExShock$ are significant at the 1% level.[39]

4.3.6 Further Robustness Checks

In this subsection, we report a series of additional robustness checks. For the sake of brevity, the details are discussed in the appendix. Appendix F.6 confirms the robustness when we non-

[39] 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 pre-trends of MR for the full sample. Columns (4)-(6) include 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 with and without these controls. We also 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.

parametrically control for the initial size of the agricultural sector or the tradable sector. The findings alleviate the concern that our baseline results are driven by the differential pre-trends in the regions with a larger agricultural sector or a larger non-traded sector. Appendix F.7 considers the reduction in trade policy uncertainty associated with the permanent normal trade relation (PNTR) granted by the US upon China's accession to the WTO. We construct alternative export demand shocks by exploiting the exogenous variation of NTR tariff gaps as is in Pierce and Schott (2016) and Handley and Nuno (2016), and investigate their effects on IMR during the 2000s. Note that our IV strategy aims at isolating the exogenous variation in exports. This goal can be achieved by exploiting various exogenous demand shifters so we prefer actual tariff changes, but as long as NTR gap is uncorrelated with other aggregate supply and demand shocks, it would be a valid instrument. We find that the results are robust to this alternative IV formulation, which is reassuring. Appendix F.8 investigates the potential omitted effects from other policy reforms upon China's WTO accession, including the removal of restrictions on direct trading, the change in export licence requirement, the quota reduction under the Muti-fiber Agreement, and the FDI liberalization. We conduct numerous checks and mitigate the concern that these alternative trade shocks confound our baseline findings.

4.4 Results for Specification 2: Pollution Concentration Channel

So far we have explored the "reduced form" effect of export shocks on mortality, but ignored the channels through which export shocks operate. In this section, we investigate the effect that export shocks have on mortality through pollution concentration. Table 7 reports the regression results of equations (10), i.e. the effects of the two types of export shocks on the air concentration of SO_2 (Panel A) and $PM_{2.5}$ (Panel B). We run the IV regressions in this table with the instruments described in Section 3.3. In the left panel, $PollExShock$ is measured by the export-induced emission per worker of the pollutant that is more related to the pollution outcome of interest. Specifically, $PollExShock^{SO_2}$ ($PollExShock^{TSP}$) is taken as the regressor when SO_2 ($PM_{2.5}$) concentration is the outcome measure. In the right panel, we use the first principal component, i.e., $PollExShock^{PCA}$, as the explanatory variable.

Across different specifications, we obtain consistent findings that $PollExShock$ has a positive and significant effect on pollution concentration for both pollutants, while $ExShock$ 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 $PollExShock$ causes SO_2 concentration to rise by an additional 6.3 $\mu g/m^3$, while a one 2000's standard deviation increase in $ExShock$ causes concentration to fall by 2.1 $\mu g/m^3$ (not statistically significant). These changes represent respectively 19% and 6.3% of the standard deviation of SO_2 concentration change during 2000-2010. The estimates in column (9) of Panel B suggest that changes in $PM2.5$ concentration induced by a standard deviation increase in $PollExShock$ is 1.7 $\mu g/m^3$, which amounts to 17.7% of the standard deviation of the decadal change in $PM_{2.5}$ concentration. The corresponding numbers for a standard deviation increase in $ExShock$ are -1.6 $\mu g/m^3$ (not statistically significant) and 16.8%, respectively.[40]

Table 8 presents the regression results for equation (11), where 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. Panels A and B correspond to the effects of SO_2 and $PM_{2.5}$, respectively. For the 2SLS specifications, we use $Poll\widehat{ExShock}$ and $\widehat{ExShock}$ as instruments for pollution concentration and export income shock. [41]

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 as in columns (2) and (4). This is because our system of equations (10) and (11) addresses two issues: (i) it provides an instrument for $\Delta PollConc^p_{it}$, i.e. $PollExShock$ which affects infant mortality only through its effect on pollution; (ii) it allows $ExShock$ 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 $PM_{2.5}$. Compared to column (2), the specification in (4) further controls for the initial pollution level of a prefecture, i.e., $PollEmpl$, which absorbs some variation in $PollExShock$, resulting in a weaker first stage as reflected by the F-statistic. With this issue in mind, the more conservative estimates in column (2) will be employed when we gauge the magnitude of the effects.

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. Our estimates in column (2) imply that the elasticity of IMR to SO_2 is 0.81, while the elasticity of IMR to $PM_{2.5}$ is 1.9. Table 9 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 $PM_{2.5}$ and our estimate of 1.9 is higher than estimates based on TSP and PM_{10}. 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 et al. (2002). Although not directly comparable, a handful of cross-sectional

[40]In appendix Table A.14, we establish the robustness of the relationship between export shocks and pollution concentration by repeating the checks discussed in Section 4.3.

[41]For example, the increase in migration induced by export expansion may have an independent effect on IMR. Our identification assumption requires $ExShock$ to fully capture this potential omitted channel, and hence coefficient ρ_1 in equation (11) is not confounded by such forces.

studies on the impact of TSP on total adult mortality in China provide a useful benchmark. As summarized by Cropper (2012) these studies report semi-elasticities 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 3.3% (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. [42]

4.5 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 from DPS that has been previously explored in Chen et al. (2013) and provides information on causes of death. For the purpose of the analysis, we group the causes into six categories: cardio-respiratory illnesses, infant-specific causes (including congenital anomalies and perinatal conditions), digestive illnesses, infectious illnesses, malnutrition, and external causes (including accidents and violence).[43] If $PollExShock$ indeed affects IMR through air pollution, the effect should be more pronounced on mortality related to cardio-respiratory illness. However, if $PollExShock$ is correlated with unobserved prefecture-specific shocks that have independent effects on health outcomes (e.g., changes in provision of medical service), we may find a significant but spurious relationship between IMR and $PollExShock$ for other causes which are less likely to be associated with air pollution. In Table 10, we find that only mortality due to cardio-respiratory causes is sensitive to the pollution content of export. Infant mortality related to other causes does not appear to be sensitive to export shocks.

5 Discussion of Overall Trade Effects and Concluding Remarks

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

[42] He et al. (2016) find that the elasticity of mortality rate of age 0-4 to PM10 is 1.9.

[43] 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.

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 isolate export expansion due to 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. A one standard deviation increase in that shock increases infant mortality by 4.1 deaths per thousand live births, which is about 23% of the standard deviation of infant mortality change during the period. 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, $PollExShock$ and $ExShock$ in order to assess their combined effect on the decline in IMR in different prefectures. 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 5. The figure reports, for each prefecture, the value of $\hat{\alpha}_1 PollExShock^p_{it} + \hat{\alpha}_2 ExShock_{it}$ from specification in column (1) of Table 5 using the value of the shocks for the period 2000-2010.

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 at the national level. 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 1990-2010, with an average number of births of 48,413 per prefecture per year, our calculations imply that $PollExShock$ caused a total of 899,661 extra deaths (44,983 per year).[44] Although the effect of $ExShock$ is not always significant, we

[44] Note that by construction, $PollExShock^{PCA}$ is demeaned. To retrieve the level effect, we calculate the average

still employ it to quantify its beneficial effect on mortality. The effect of *ExShock* reduced the number of deaths by 96,573 in 1990-2010. The net effect expressed in percentage was an increase in mortality by 0.24 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 substantially larger, which is reasonable if we consider that exports grew at an extraordinary pace during that period. Our effect is about one quarter relative to the one found by Jayachandran (2009) of an increase in infant mortality by one percentage point due to Indonesian wildfires.

The main take-away from this paper is that in the years 1992-2010 regions in China more involved in the export expansion might have greatly benefited from increased access to world markets, but they paid a cost in terms of a relatively higher infant mortality and more rapidly deteriorating environmental quality.

pollution export shock according to $\alpha^{SO2}\mu^{SO2}/\sigma^{SO2} + \alpha^{TSP}\mu^{TSP}/\sigma^{TSP} + \alpha^{NO2}\mu^{NO2}/\sigma^{NO2}$. α^{p} denotes the elements of the eigenvector corresponding to the first principle component. μ^{p} and σ^{p} denote mean and standard deviation of different pollution export shocks, respectively. The average pollution export shock is 2.24.

The total number of extra deaths is calculated by multiplying the average of pollution export shock by the coefficient 2.44 and the number of births 48,413. The number is then divided by 1000 because mortality is expressed relative to 1000 live births. The resulting number is multiplied by 20 years (two decades) 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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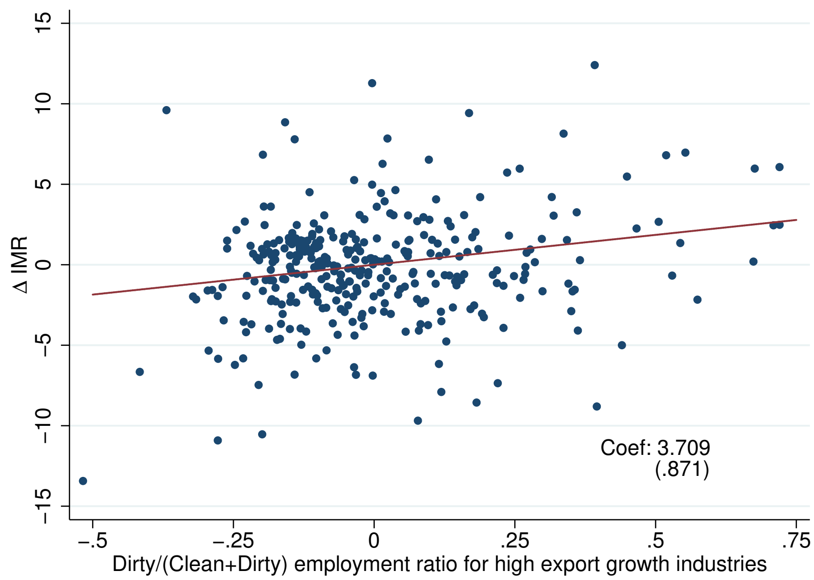
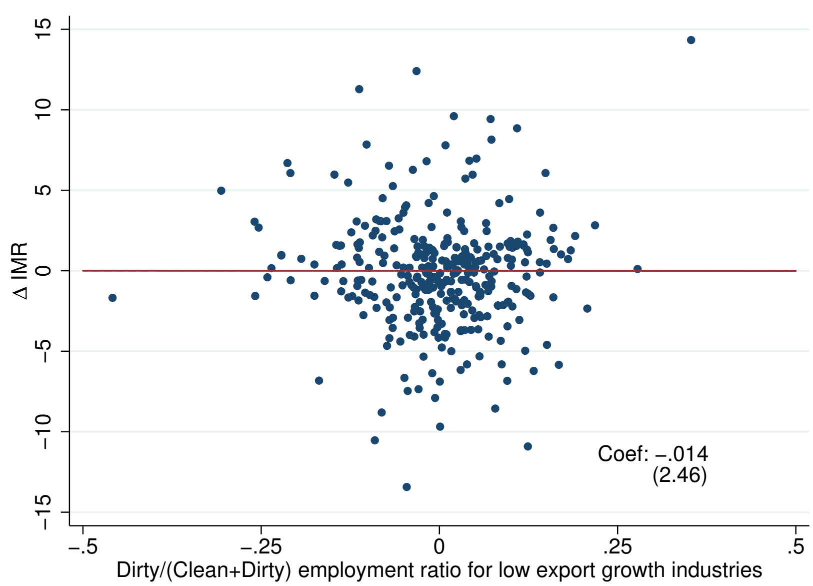
6 Figures

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: Mechanism relating Export Shocks to Mortality

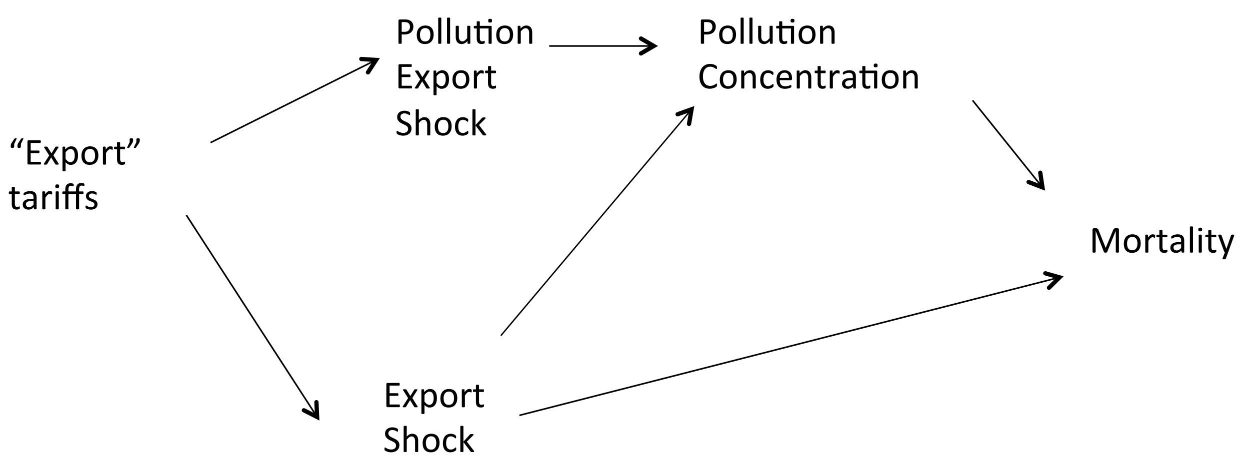
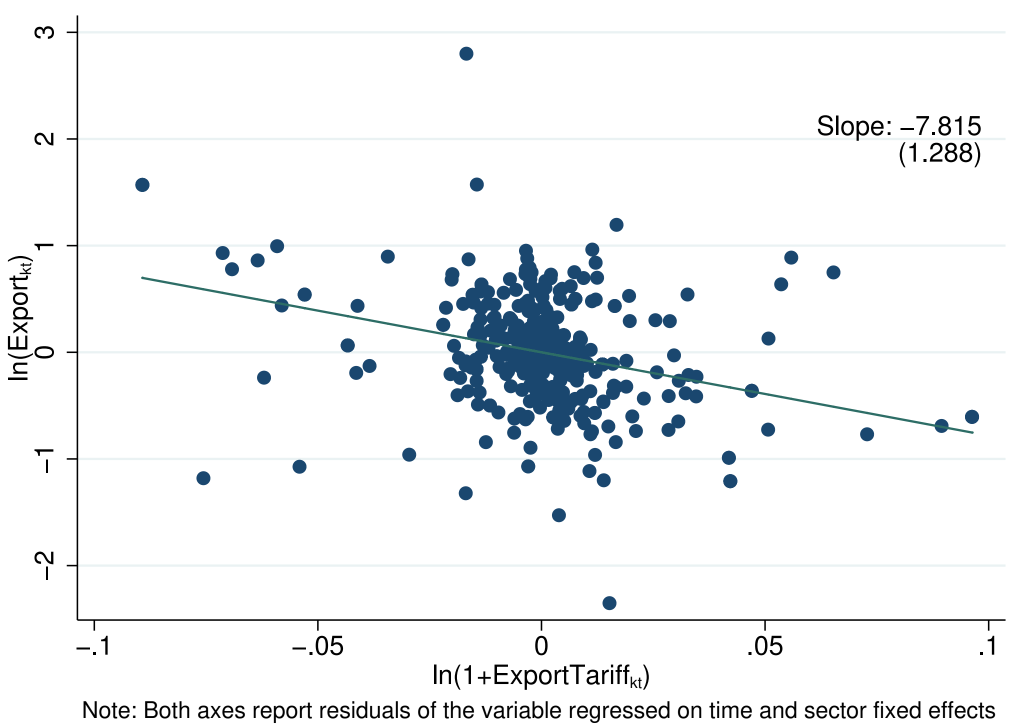
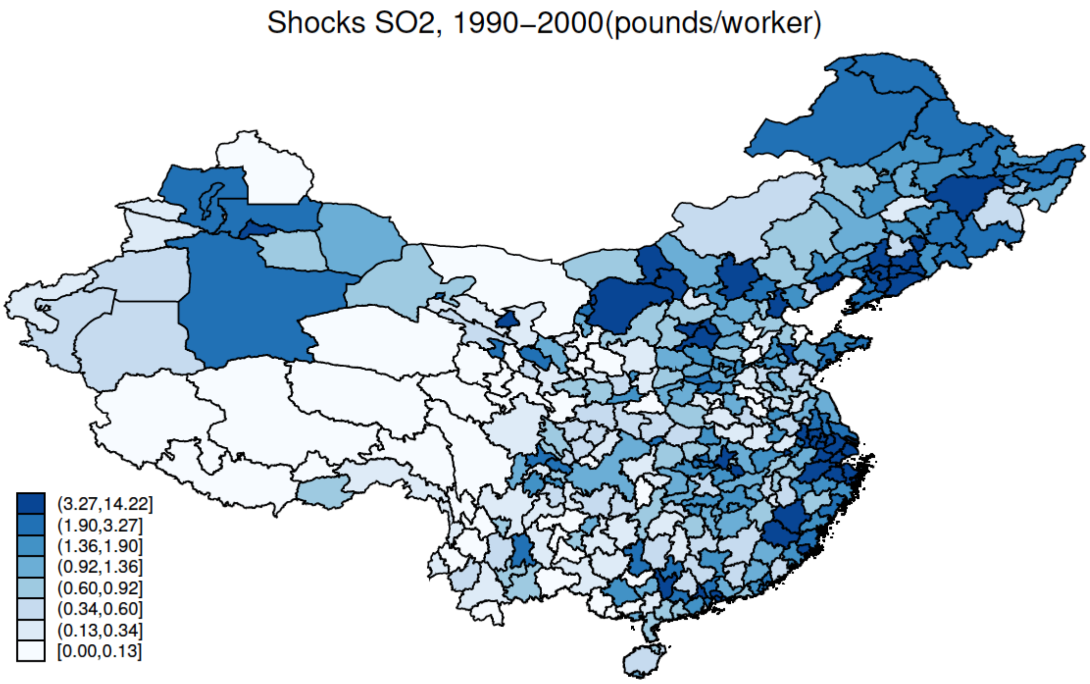


Figure 3: The relationship between Log(Exports) and Log(1+ExportTariff)



Notes: The figure displays the residual scatter plot based on regression 6. The data of export and tariff cover 148 3-digit CSIC industries over the period 1992,2000 and 2010.

Figure 4: Distribution of Export Pollution Shocks over Decades, SO2



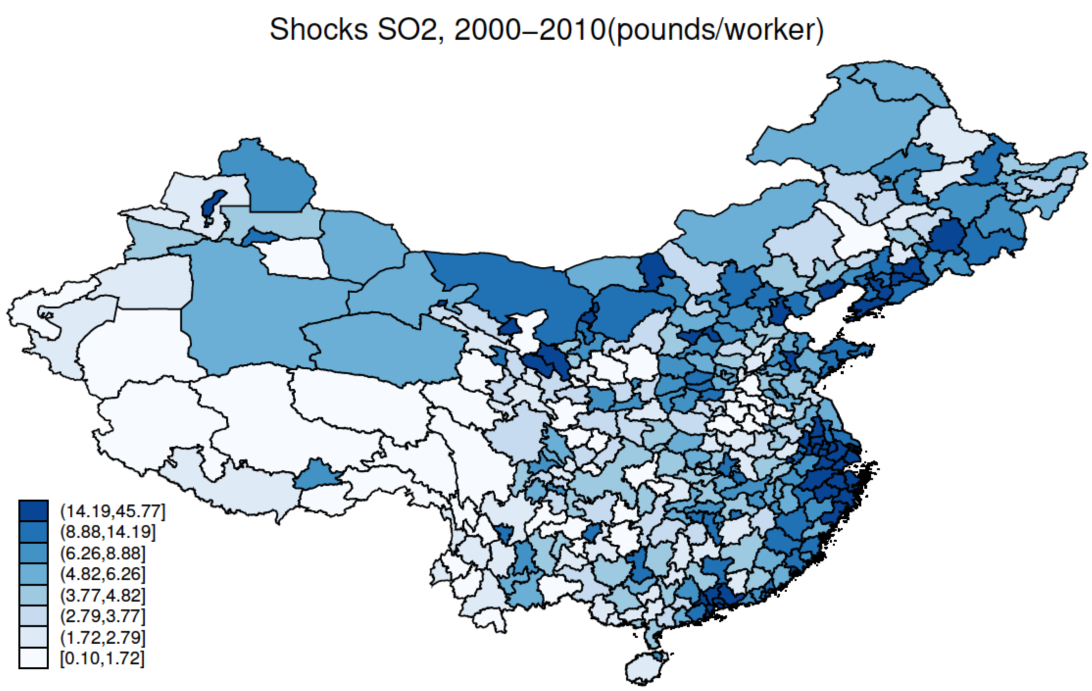
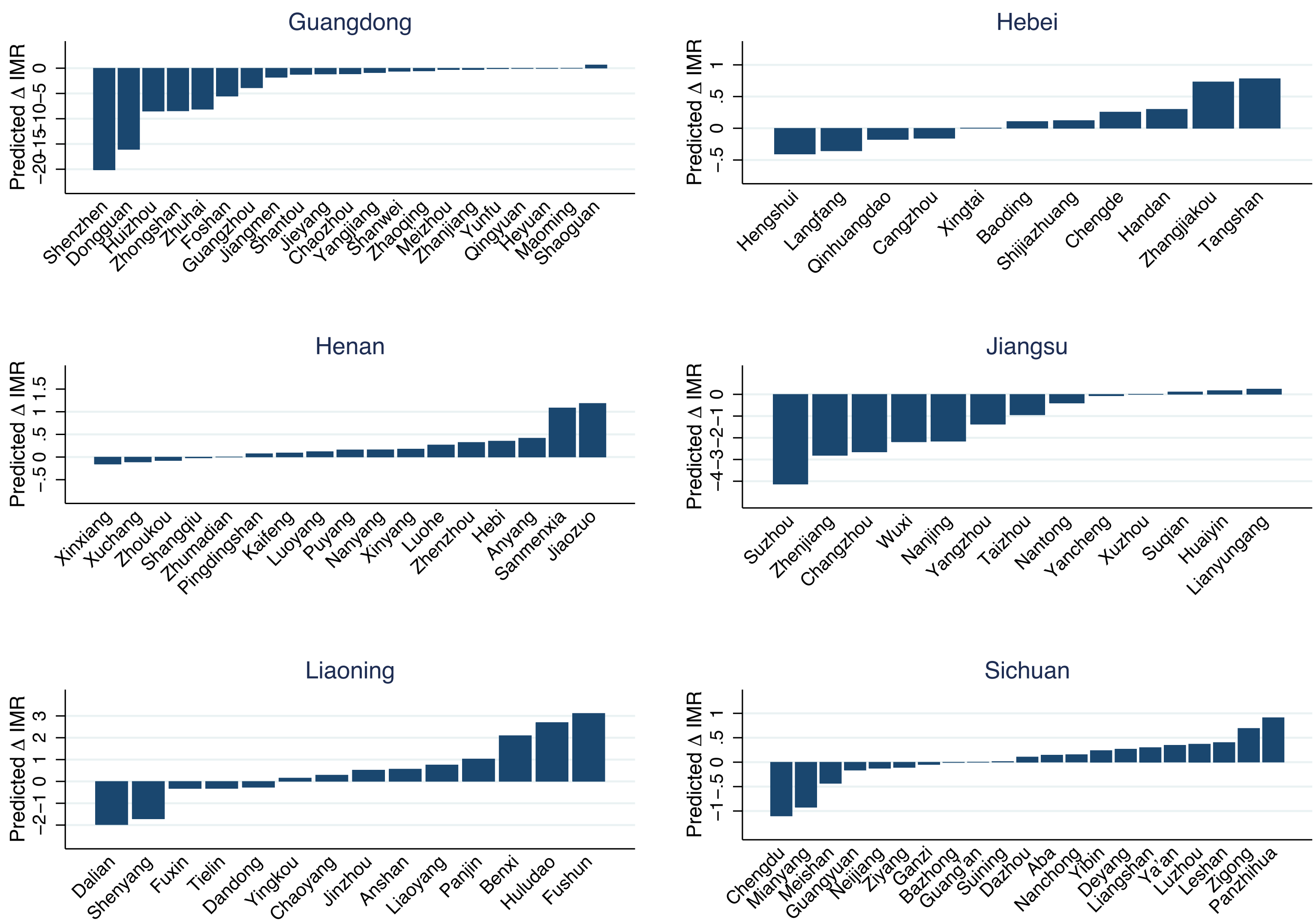


Figure 5: The combined effect of $PollutionExportShock_{it}$ and $ExportShock_{it}$ on IMR



Notes: Each bar represents for each prefecture the predicted change in IMR, i.e.$\hat{\alpha}_1 PollExShock^p_{it} + \hat{\alpha}_2 ExShock_{it}$, from the specification in column (7) in Table 3 using the value of the two shocks for the period 2000-2010.

7 Tables

Table 1: 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
ΔIMR, 90-10	-10.753	18.065	-29.307	-16.224	-9.097	-3.226	4.546
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)							
PCA, 90-00	-0.802	0.686	-1.276	-1.204	-1.009	-0.662	-0.036
PCA, 00-10	0.802	2.005	-0.870	-0.519	0.187	1.337	3.499
PCA, 90-10	0.000	1.699	-1.239	-1.030	-0.590	0.330	1.844
$SO2$, 90-00	2.199	3.468	0.074	0.360	1.219	2.681	5.408
$SO2$, 00-10	8.109	7.990	1.582	2.984	5.494	9.997	18.540
$SO2$, 90-10	5.154	6.830	0.246	1.017	2.838	6.183	12.138
TSP, 90-00	2.133	2.913	0.091	0.374	1.229	2.624	5.164
TSP, 00-10	9.821	9.209	2.241	3.678	6.794	12.136	21.983
TSP, 90-10	5.977	7.836	0.267	1.165	3.179	7.875	14.817
$NO2$, 90-00	0.609	0.813	0.022	0.114	0.348	0.831	1.637
$NO2$, 00-10	2.768	2.786	0.517	0.984	1.889	3.457	6.699
$NO2$, 90-10	1.689	2.318	0.062	0.312	0.882	2.109	4.099
Panel D: Export Shocks (1000 dollars per worker)							
ExShock, 90-00	0.203	0.271	0.007	0.039	0.105	0.247	0.511
ExShock, 00-10	1.505	2.316	0.227	0.420	0.824	1.615	3.241
ExShock, 90-10	0.854	1.773	0.025	0.095	0.339	0.878	1.994

Table 2: Correlation of Industry Characteristics

	Pollution Intensity (PCA)		$\Delta ln(1+Tariff)$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Migrant Share	-0.248***		-0.072				
	(0.000)		(0.219)				
Rural Hukou Share		-0.066		0.027			
		(0.259)		(0.639)			
Pollution Intensity (PCA)					-0.0164		
					(0.779)		
Δ ln Output per worker						-0.002	
						(0.980)	
Δ ln Domestic demand per worker							0.040
							(0.631)

Notes: The data on share of migrant and share of workers without Hukou are obtained from the 2000 population census. The data on change in log output per worker and change in log domestic demand per worker are constructed based on 2000 and 2010 data from Chinese Industrial Annual Survey. p-value indicating the statistical significance in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: 2SLS Estimates			
Dep. Var: ΔIMR							
$PollExShock^{PCA}$	1.946***	2.011***			1.511***	2.674***	2.440***
	(0.233)	(0.443)			(0.490)	(0.605)	(0.620)
$ExShock$			1.289***	0.383	0.398	-0.821	-0.687
			(0.323)	(0.537)	(0.350)	(0.508)	(0.532)
Angrist-Pischke F-statistic: $PollExShock$	364.3	111.1			194.7	114.1	109
Angrist-Pischke F-statistic: $ExShock$			342.1	193.6	360.4	290.8	265.2
				Panel B: First Stage Estimates			
Dep. Var: $PollExShock^{PCA}$							
$Poll\widehat{ExShock}^{PCA}$	0.981***	0.910***			0.909***	0.904***	0.930***
	(0.051)	(0.086)			(0.083)	(0.106)	(0.110)
$\widehat{ExShock}$					0.079	0.008	-0.011
					(0.049)	(0.049)	(0.053)
Dep. Var: $ExShock$							
$Poll\widehat{ExShock}^{PCA}$					-0.176***	-0.148**	-0.157**
					(0.064)	(0.054)	(0.061)
$\widehat{ExShock}$			1.238***	1.190***	1.364***	1.276***	1.283***
			(0.067)	(0.086)	(0.081)	(0.091)	(0.093)
Region×Year	Y	Y	Y	Y	Y	Y	Y
Time-varying Controls		Y		Y		Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}		Y		Y		Y	Y
$PollEmpl^{PCA}$							Y
N	680	673	680	673	680	673	673

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with 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 Future Shocks

Dep. Var: ΔIMR	(1)	(2)	(3)
$PollExShock^{PCA}_{t+1}$	-0.290		0.185
	(0.453)		(0.700)
$ExShock_{t+1}$		-0.382	-0.503
		(0.264)	(0.426)
Angrist-Pischke F-statistic: $PollExShock$	341.1		210
Angrist-Pischke F-statistic: $ExShock$		339.3	371
Region×Year	Y	Y	Y
N	673	673	673

Notes: All regressions are weighted by population of age 0. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Change in Infant Mortality Rate and Shocks: Alternative Specifications and Measures, 2SLS

Dep. Var: ΔIMR	Prov $\times$Year Fixed Effects (1)	Unweighted Regression (2)	Without Normalization (3)	Neighboring Shocks (4)	Combined Local and Neighbors (5)	IO-adjusted Shocks (6)	Actual Export Expansion (7)	Export Share Weights (8)	Export Shock by Group (9)	Output Shocks (10)
$PollExShock^{PCA}$	1.573***	2.322***	0.727***	1.745***	3.253***	1.887***	7.067***	0.490***		
	(0.507)	(0.453)	(0.266)	(0.569)	(0.802)	(0.661)	(2.470)	(0.187)		
$ExShock$	-0.376	-0.808**	0.008	-0.420	-0.637**	0.073	-2.402***	-1.080***		
	(0.482)	(0.407)	(0.543)	(0.611)	(0.296)	(0.304)	(0.928)	(0.288)		
$WindPollExShock^{PCA,N}$				2.453***						
				(0.767)						
$ExShock^{N}$				-0.933***						
				(0.305)						
$ExShock^{D}$									6.434***	
									(1.491)	
$ExShock^{C}$									-1.588***	
									(0.448)	
$PollOutputShock^{PCA}$										6.617***
										(1.828)
$OutputShock$										-0.370***
										(0.126)
Region$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	673	673	672	673	673	673	340	340	673	340

Notes: All regressions except column (2) 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 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. All columns include the controls and fixed effects in column 8 of Table 3. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 5 (Cont.) Change in Infant Mortality Rate and Shocks: Alternative Specifications and Measures, 2SLS

Dep. Var: ΔIMR	Energy Production (11)	Import Shocks (12)	High-skill Shock (13)	Share of Ownership (14)	TCZ (15)
$PollExShock^{PCA}$	2.028***	3.314***	2.206***	1.824***	2.315***
	(0.517)	(0.921)	(0.585)	(0.517)	(0.597)
$ExShock$	-1.796***	-0.950*	2.341*	-1.789***	-0.685
	(0.430)	(0.564)	(1.199)	(0.414)	(0.543)
$\Delta EnergyProd$	0.268**				
	(0.129)				
$PollImShock^{PCA}$		-0.932**			
		(0.433)			
$HighSkillShock$			-7.339**		
			(2.856)		
$\Delta Share\ SOE$				6.969**	
				(3.416)	
$\Delta Share\ Foreign$				0.189	
				(3.458)	
TCZ					2.669***
					(0.726)
Region×Year	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y
N	340	673	673	340	673

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Change in Infant Mortality Rate and Shocks by Gender and Age Group: 2SLS

	Age 0			Age 1-4		
	All	Boys	Girls	All	Boys	Girls
Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)	(6)
$PollExShock^{PCA}$	2.371***	2.075***	2.677***	0.165***	0.137***	0.165***
	(0.764)	(0.649)	(0.922)	(0.038)	(0.033)	(0.048)
$ExShock$	-0.429	-0.534	-0.303	-0.120***	-0.101***	-0.127***
	(0.728)	(0.633)	(0.817)	(0.030)	(0.028)	(0.037)
Angrist-Pischke F-statistic: $PollExShock$	109	110.5	107.5	174.5	112.9	108.5
Angrist-Pischke F-statistic: $ExShock$	265.2	264	266.7	311.9	304.9	297.5
Region×Year	Y	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y	Y
N	673	673	673	673	673	673

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Changes in Pollutant Concentration and Shocks: 2SLS

Panel A: *Dep. Var:* $\Delta SO2$	*SO2 PollExShock*			*PCA PollExShock*		
	(1)	(2)	(3)	(4)	(5)	(6)
PollExShock	0.760***	1.073***	0.791**	3.359***	4.763***	3.419**
	(0.254)	(0.258)	(0.355)	(1.061)	(1.116)	(1.493)
ExShock		-1.514**	-0.909		-1.709**	-1.006
		(0.752)	(0.913)		(0.751)	(0.900)
Angrist-Pischke F-statistic: *PollExShock*	50.16	43.44	39.63	66.19	60.20	57.89
Angrist-Pischke F-statistic: *ExShock*		182.8	168		188.3	173
N	268	268	268	268	268	268
Panel B: *Dep. Var:* $\Delta PM2.5$	*TSP PollExShock*			*PCA PollExShock*		
	(7)	(8)	(9)	(10)	(11)	(12)
PollExShock	0.186***	0.251***	0.190**	0.831***	1.390***	0.890*
	(0.056)	(0.076)	(0.074)	(0.264)	(0.416)	(0.515)
ExShock		-0.810	-0.705		-1.001	-0.818
		(0.551)	(0.566)		(0.609)	(0.635)
Angrist-Pischke F-statistic: *PollExShock*	349.9	379.3	425.8	62.41	66.36	45.69
Angrist-Pischke F-statistic: *ExShock*		187	114.4		167.4	121.3
N	340	340	340	340	340	340
Region(×Year)	Y	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y
PollEmpl			Y			Y

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Changes in Infant Mortality Rate and Changes in Pollutant Concentration: 2SLS

Dep. Var: ΔIMR	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
Panel A: SO2 Concentration and IMR				
$\Delta SO2$	-0.020	0.265*	-0.020	0.432*
	(0.033)	(0.138)	(0.034)	(0.251)
$ExShock$	-0.078	0.113	-0.078	-0.017
	(0.412)	(0.431)	(0.409)	(0.453)
Angrist-Pischke F-statistic: $PollExShock$		10.20		3.713
Angrist-Pischke F-statistic: $ExShock$		214.8		183.2
N	268	268	268	268
Panel B: PM2.5 Concentration and IMR				
$\Delta PM2.5$	0.046	1.308**	0.033	2.343*
	(0.078)	(0.514)	(0.080)	(1.368)
$ExShock$	-1.550***	-0.471	-1.510***	0.038
	(0.450)	(0.685)	(0.424)	(1.224)
Angrist-Pischke F-statistic: $PollExShock$		11.16		3.322
Angrist-Pischke F-statistic: $ExShock$		248.6		163.6
N	340	340	340	340
Region($\times$Year)	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y
$PollEmpl$			Y	Y

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 9: 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 10: Changes in Infant Mortality Rate and Shocks by Causes of Death: 2SLS

Dep. Var: ΔIMR^C	Cardio-Respiratory (1)	Infant Specific (2)	Digestive (3)	Infectious (4)	External Causes (5)	Malnutrition (6)
$PollExShock^{PCA}$	2.300**	-0.291	0.207	0.197	1.512	-0.289
	(0.995)	(4.220)	(0.330)	(0.369)	(1.374)	(0.342)
$ExShock$	-5.536***	-4.414	-0.196	-0.196	-2.659	0.747
	(1.904)	(8.687)	(0.409)	(0.819)	(2.777)	(0.691)
Angrist-Pischke F-statistic: $PollExShock$	118.3	118.3	118.3	118.3	118.3	118.3
Angrist-Pischke F-statistic: $ExShock$	856.3	856.3	856.3	856.3	856.3	856.3
Region	Y	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y	Y
N	118	118	118	118	118	118

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Appendix not for Publication

A Event Study: the 2002 US Steel Safeguard Measures

In this appendix we perform a separate exercise aimed at answering the question: are exports shocks generated by trade policy in the rest of the world large enough to affect local pollution measures in China? We investigate the issue through a specific event, i.e., the US imposition of safeguard tariffs on imports of steel products in March 2002 (and its removal in December 2003). On June 28, 2000, the US Trade Representative (USTR) requested that 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 October 22, 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 March 20, 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[45] (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 March 28, 2002 and introduced final safeguard measures on September 29, 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 covered by safeguard tariffs. China also initiated its own safeguard measures on May 20, 2002. On December 4, 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.[46] We exploit this event to detect whether a temporary protection measure in the US that raised import tariffs on several

[45] 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%.

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

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 prefectures relative to other prefectures before and after the steel safeguards. We use the daily data on air pollution index (API), an overall measure of ambient air quality. API data are obtained from the MEP of China. The dataset records the API of major prefectures in China starting from June 5th, 2000. The number of prefectures 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.[47]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)[48] and the dummy $NoSG$ is equal to 1 in the period before the investigation or 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.)[49] α_i is a prefecture dummy which controls for the time-invariant prefecture-specific factors that affect the air quality. ϕ_{ry} is the region-year fixed effects which in effect capture the unobserved region-specific shocks that have independent effects on API. γ_{rm} represents region-month fixed effects which account for the region-specific seasonal factors that affect API. [50] Standard errors are clustered at the prefecture level. The different specifications in Table A.1 employ different time windows 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 prefectures. The effect is not very large, but strongly significant. Column (8) of Table A.1 extends the window to August 2005 and 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. Figure A.2 shows the estimates from the following specification

$$API_{it} = \sum_{\tau} \lambda_\tau ShareSteel_i + \alpha_i + \phi_{ry} + \gamma_{rm} + \varepsilon_{it} \ ,$$

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

[48]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.

[49]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).

[50]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).

where λ_τ's reflect the conditional correlation between the API and steel employment share that vary across quarters. Consistent with the findings in Table A.1, we find the API is lower during the period with steel safeguards.

B Theoretical Derivation of Export Shocks

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 fixed.[51] 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:

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

We assume that there is a large non-manufacturing sector that also employs only labor and that determines the wage w_i.[52] 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 $Y_{ik} = \sum_\omega p_{ik}(\omega) Q_{ik}(\omega) = w_i L_{ik}$.

[51] 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 (2016).

[52] 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.

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:

$$w_i L_{ik} = \sum_{j=1}^{N} X_{ijk} = \sum_{j=1}^{N} \lambda_{ijk}\beta_k Y_j \ . \tag{14}$$

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

B.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 (14) gives

$$dY_{ik} = dX_{iRk} = \frac{X_{iRk}}{X_{CRk}} dX_{CRk} \ , \tag{15}$$

where dX_{CRk} is the change in exports of good k from China to the ROW *due to a change in trade cost.*[53] More specifically,

[53]More specifically, equation (15) is derived as follows:

$$d\lambda_{iRk} = -\frac{\theta\lambda_{iRk}}{\tau_{Rk}} d\tau_{Rk} + \frac{\theta\lambda_{iRk}\sum_{i'\in C}\lambda_{i'Rk}}{\tau_{Rk}} d\tau_{Rk} = -\theta(1-\lambda_{CRk})\lambda_{iRk}\frac{d\tau_{Rk}}{\tau_{Rk}} \ , \tag{16}$$

where C is the set of regions in China. In this derivation, it is key to impose the contemporaneous change in tariffs in the rest of the world to be the same for all regions in China. Analogously, the change in China's share in the rest

$$dX_{CRk} = X_{CRk} \times \hat{\tau}_{Rk} \tag{17}$$

Then, the total change in emissions is given by:

$$dP_i = \sum_k \gamma_k \frac{X_{iRk}}{X_{CRk}} dX_{CRk} \ . \tag{18}$$

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 prefectures are different in size, the pollution concentration and and export shocks are related as follows:

$$dC_i \propto \sum_k \gamma_k \frac{X_{iRk}}{X_{CRk}} \frac{dX_{CRk}}{L_i} \ . \tag{19}$$

where L_i denotes the size of prefecture i.

Equation (19) 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 shock 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.

C Data Appendix

C.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.

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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 (16) to find:

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

Simple manipulation yields equation (15).

C.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.

C.3 Computation of Three-Digit Industry Emission Intensity

Pollution intensity for each pollutant p, of a 3-digit CSIC industry k, is imputed following these steps: (i) using industry output as weight,[54] 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 changing industry pollution intensity over time, we use the 1996 and 2006 data from MEP and construct measures for each decade t. Pollution intensity $\gamma_{kt}^{p,MEP}$ is employed to build pollution export shocks as is discussed in Section 3.

C.4 Death Records in Population Census

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 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.

[54]Data on output by industry is from the Chinese Industrial Annual Survey.

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.

C.5 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:

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

C.6 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.[55] The wind direction is categorized into 37 groups, i.e., $d \in \{0, \frac{\pi}{36}, ..., \frac{35\pi}{36}, No\ Wind\}$. 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.[56] For each prefecture, we calculate the share of days that the wind direction is d

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

[56] The nearest weather station is identified as the one with the shortest distance to the centroid of a prefecture. We obtain similar results using the data from the first and second most nearest weather stations.

for each decade, i.e., 1990-2000 and 2000-2010. It is denoted by $s_{it,d}$.

C.7 Other Demographic and Socioeconomic Data

We collected other demographic and socioeconomic variables at the 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 the World Port Index. In addition, for the period of 2000 to 2010, 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.[57] We also obtain the transaction-level export data from China's General Administration of Customs to construct actual dollar value of export and pollution content of export at the prefecture level for 2000 and 2010.

C.8 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 export shock is defined as follows:

$$ExShock_{i,t}^{N} = \sum_{n \in Neighbor_i} \psi_{int} ExShock_{nt}^{p} ,$$

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

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

$$WindPollExShock_{i,t}^{p,N} = \sum_{d \in \{0, \frac{\pi}{36}, \ldots, \frac{35\pi}{36}, NW\}} \sum_{n \in Neighbor_i} \pi_{int,d} PollExShock_{nt}^{p} .$$

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

$$\pi_{int,d} = \frac{s_{nt,d} w_{in,d}}{\sum_d \sum_r s_{nt,d} w_{in,d}} ,$$

where $s_{nt,d}$ denotes the share of days in which the wind direction is d in neighboring prefecture n and decade t. $w_{in,d}$ captures the weight of different wind directions. It is determined by the

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

relative position between i and n and the wind direction in n, and it is constructed as follows:

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

where $\theta_{in,d}$ denotes the *absolute value* of the angle between neighboring prefecture n's angular position and its wind direction d. The example in Figure A.4 illustrates how $\theta_{in,d}$ is calculated. The green triangle represents a prefecture, who has three neighboring prefectures (n = 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 $w_{in,d} = 1$ if prefecture i is in the downwind position of n, i.e., $\theta_{in,d} = 0$, and $w_{in,d} = 0$ if prefecture i is in the upwind position of n, i.e., $\theta_{in,d} = \pi$. This weighting scheme is intuitive. Prefecture i receives more cross-border pollution from prefecture n if i is located downwind of n more often, i.e., $s_{nt,d}w_{in,d}$ is larger.

C.9 Input-Output Tables

To construct the alternative export shocks as described in Section 4.3.3, 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.

D 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.

D.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 $PM_{2.5}$, 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 $AQI = IAQI^{PM_{2.5}}$ conditional on the main pollutant being $PM_{2.5}$.

We obtain the daily data from MEP for 2014. The hourly data from US Embassy is aggregated to daily data, and converted to $IAQI^{PM_{2.5}}$ using the conversion table provided by MEP. The summary statistics of the two data series are presented in Table A.3. We find that, conditional on that the main pollutant being $PM_{2.5}$, the correlation of the two series is very high, ranging from 0.94 for Chengdu to 0.97 for Shanghai. The average $IAQI^{PM_{2.5}}$ 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 $PM_{2.5}$ (PM_{10}) Concentration

The cities in China started to monitor $PM_{2.5}$ in 2013. Until then, only the concentration level of PM_{10}, the particulate matters up to 10 micrometers in size, was reported. As the $PM_{2.5}$ belongs to the PM_{10}, the concentration level of the former should always be smaller than the latter. It is taken as strong evidence for data manipulation if we detect the concentration level of PM_{10} reported by MEP is smaller than that of $PM_{2.5}$ reported by US Embassy. As is shown in Table A.4, the official data of $PM_{2.5}$ track the US Embassy data closely in 2013. In addition, we fail to find any case such that the concentration level of PM_{10} reported by MEP is smaller than that of $PM_{2.5}$ reported by US Embassy.

D.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

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

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.[58]

Figure A.5 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).[59] 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 result, the actual population size is larger than the predicted population size.

E 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 and its employment share. Specifically, we estimate the following regression[60]

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

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.

[58]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.

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

[60]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.

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

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

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 share.

F Additional Results

F.1 Multicollinearity Problem and Monte Carlo Simulation

The correlation between *PollExShock* and *ExShock* is 0.74, leading to a concern about multicollinearity. In the following, we conduct Monte Carlo simulations to assess the sensitivity of our results to the potential multicollinearity problem. In particular, we consider the following reduced-form model:

$$y_{it} = \beta_1 x_{1,it} + \beta_2 x_{2,it} + \varepsilon_{it}, \tag{20}$$

where x_1 and x_2 are the actual data corresponding to $\widehat{PollExpShock}$ and $\widehat{ExShock}$. The error term ε is drawn from the normal distribution $N(0, \sigma^2)$, where σ is the standard deviation of the residuals from the baseline model (i.e., regression in column (7) of Table 3). We consider two cases with different values of β_1 and β_2. For each case, we simulate 500 datasets. By design, the simulated data has the same number of observations and the same correlation of the two variables of interest as in the actual data.

Case I: $\beta_1 = 2.5$ and $\beta_2 = 0$. We estimate equation (20) using the 500 simulated datasets. Column (1) of Table A.5 reports the average and the standard deviation of the estimates of β_1 and β_2. We find that on average, both estimates are very close to their true values. Column (2) drops x_2 from regression. The average of $\hat{\beta}_1$ barely changes since $\beta_2 = 0$. In column (3), we estimate the misspecified model with x_1 omitted, and find that $\hat{\beta}_1$ is severely biased. This finding echoes the results in column (3) of Table 3 in the main text, suggesting that the estimate of export income effect is severely biased without controlling for the pollution effect.

Case II: $\beta_1 = 2.5$ and $\beta_2 = -1$. Multicollinearity leads to noisy estimates. If it is a valid concern, we may obtain statistically insignificant coefficients even if the true effects are non-zero. (In our context, one may worry that the insignificant coefficient on $ExShock$ is a result from the multicollinearity problem.) To alleviate the concern, we simulate datasets by setting $\beta_2 = -1$. Columns (4) estimates equation (20). Again, we find that both estimates are very close to their true value. More importantly, both estimates are statistically significant at the 1% level. We take this finding as suggestive evidence that our identification is unlikely to be hindered by the correlation between the two variables.

The main takeaways from this exercise are twofold. First, it is exactly because of the correlation between $Poll\widehat{ExpShock}$ and $\widehat{ExShock}$, the estimated export income effect has a wrong sign in a misspecified model without accounting for the pollution effect. Second, despite the high correlation, there is sufficient statistical power to identify their independent effects.[61]

F.2 Rotemberg Weights

In this section, we compute the Rotemberg weights of export pollution shocks and export shocks with controls, aggregated across time periods.[62] The industry-specific Rotemberg weights capture the degree of sensitivity to misspecification when the exogeneity assumption of initial industry composition fails. In particular, the 2SLS estimates are more sensitive to the bias introduced by an industry with a larger Rotemberg weight.(Goldsmith-Pinkham et al., 2018) Table A.7 reports the five industries with the highest Rotemberg weights for $PollExShock^{TSP}$ and $ExShock$, respectively. For pollution export shock, these industries are graphite and carbon products, leather

[61] Autor et al. (2018) employ gender-specific components of import supply shocks to investigate the impacts of shifts in relative earnings of young men versus young women on marriage, fertility and children's living circumstance. Similar to our case, despite the high correlation between their by-gender measures (0.80), they are able to distinguish the independent effects.

[62] In this exercise, we adopt the measure $PollExShock^{TSP}$. Therefore, the industry-level trade shock for export pollution shock is $\gamma_{kt}^{TSP} \frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$. The industry-level trade shock for export shock is $\frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$. Different from the cases discussed in Goldsmith-Pinkham et al. (2018), we have two endogenous variables. When we construct Rotemberg weights for $PollExShock^{TSP}$, we include $\widehat{ExShock}$ as a control. Similarly, when we construct Rotemberg weights for $ExShock$, we include $Poll\widehat{ExShock}^{TSP}$ as a control. We also in include all the controls listed in column (7) of Table 3.

products, games and toys, brick and clay and related products, and refractory products.[63] The top five industries account for 29.5% of the positive weights in the Bartik estimator, which is lower than the cases studied in Goldsmith-Pinkham et al. (2018). For export shock, the top five industries are games and toys, electronic components, other plastic products, metal products for daily uses, and leather products. The sum of the Rotemberg weights of these industries amounts to 43.8% of the positive weights in the Bartik estimator.

One may worry that our baseline estimates are confounded by the prefecture-specific pre-trends that are correlated with initial shares of these industries. To allay the concern, we relate the trends of IMR to initial shares of these potentially influential industries by estimating the following regression:

$$\Delta IMR_{it} = \beta_0 + \beta_\tau EmpShare^k_{i,90} + \gamma_{rt} + \varepsilon_{it},$$

where $EmpShare^k_{i,90}$ denotes industry $k's$ share in total employment of prefecture i in 1990 (in percentage), and γ_{rt} is the region×year fixed effects.[64] We allow the coefficients β_τ to vary over time, where $\tau \in \{1990, 2000, 2010\}$. We then convert the changes in IMR to levels, and the levels in 1982 are normalized to be 0. Standard errors are constructed using the delta method. Figure A.6 presents the findings for the industries listed in Table A.7. Across the industries, there are no obvious pre-trends in the pre-periods, i.e., 1982-1990. For all industries, we observe stark changes during 2000-2010, when China experienced a rapid export expansion. We consider these findings as supporting evidence that our baseline estimates are unlikely to be severely biased by confounding trends.

F.3 Dropping One Sector or Two Sectors at a Time

To assess the sensitivity of our baseline results to any specific industries, we reconstruct the trade shocks and corresponding instruments but leave out one or two 2-digit CSIC sectors at a time.[65] We repeat the regression in column (7) of Table 3 using these alternative measures of trade shocks. Columns (1) and (2) of Table A.8 report the range of the estimates for the case where we drop one sector at a time. The estimated effects of pollution export shock range narrowly from 2.098 and 2.613, and remain significant at the 1% level. Columns (3) and (4) show the ranges when we leave out two sectors at a time. The lower- and upper-bounds of the estimates are statistically indifferent. These findings alleviate the concerns that the baseline estimates are (i) driven by certain polluting industries, and (ii) confounded due to the endogeneity associated with initial employment share of several influential sectors (Goldsmith-Pinkham et al., 2018).

[63] The list include three industries with pollution intensities at the top 5 percentile. These industries are graphite and carbon products, brick and clay and related products, and refractory products.

[64] The results remain similar when we use 2000 employment share.

[65] There are 38 2-digit CSIC sectors.

F.4 Balance Test of Industry-Level Shocks

The Bartik-style instrument can be generally formulated as $\sum_k s_{ikt} g_{kt}$, where g_{kt} denotes the shock experienced by industry k and period t and s_{ikt} measures the exposure of location i to the shock. In our context, g_{kt} represents (i) the export demand shock in dollar value captured by $\frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$, or (ii) the associated pollution shock $\gamma_{kt}^p \frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$.[66] The exposure to each shock is captured by initial employment share of the industry in local economy, i.e., $\frac{L_{ik,t-1}}{L_{i,t-1}}$. As is discussed in Borusyak et al. (2018), the validity of the instrument relies on the assumption that conditional on industry controls, $\sum_k \sum_t s_{kt} g_{kt} \phi_{kt} \xrightarrow{\text{p}} 0$, where $s_{kt} = E(s_{ikt})$ measures the expected exposure to industry k in period t and $\phi_{kt} = E(s_{ikt}\varepsilon_i)/E(s_{ikt})$ is an exposure-weighted expectation of untreated potential outcomes. Put in other words, the identification relies on the assumption that, weighted by s_{kt} and conditional on industry controls, the correlation between industry-level shocks g_{kt} and unobservables ϕ_{kt} approaches zero in large sample.

To substantiate this assumption, we follow Borusyak et al. (2018) and examine the randomness of the industry level shocks by testing the shock balance with respect to various regional characteristics. This exercise also guides the choice of location-level controls. The results are presented in Table A.9. Each row reports the coefficients from regressing industry-specific average of a prefecture characteristics (residualized by region-period fixed effects) on pollution export shock, export shock, and period fixed effects. Standard errors are clustered by CSIC codes, regressions are weighted by average industry exposure, and *coefficients are multiplied by 100 for readability.* We find that conditional on export shock, the pollution-export shocks are statistically uncorrelated with all the prefecture characteristics expect $PollEmpl$.[67] For example, the third row implies that pollution export shocks are not concentrated in locations that experienced relatively faster increase in IMR in the preceding decade. These findings suggest that conditional on export shock and $PollEmpl$, pollution-export shock could be as good as randomly assigned across industries. For export shock, there are more coefficients are are statistically different from zero, albeit they are small in magnitude. For example, the fourth row suggests that export shocks tend to be larger in prefectures that were initially richer. Therefore, in most of location-level regressions, we control for these location-specific characteristics.

F.5 Statistical Inference and Industry-Level Regression

In the baseline analysis, we cluster standard errors at the province level, which allows for arbitrary within-province correlation and assumes that there is no cross-province correlation in the error terms. This assumption may be too strong if there is substantial cross-province correlation that is

[66] In this exercise, we consider TSP pollution shock. Results remain similar for SO2 or NO2 pollution shock.

[67] As shown in the first row, it is unsurprising that pollution export shocks tend to be larger in prefectures with a higher share of dirty industries, which the need of controlling for $PollEmployment_{it-1}$ in (5) for the prefecture-level regression analysis.

due to the similarity of industry structure across prefectures that are not geographically proximate (Adão et al. 2018). As a robustness check, we follow Borusyak et al. (2018) and conduct the analogous analysis at the industry level, which overcomes such concerns about statistical inference of shift-share research designs.[68] The results are reported in Table A.10. The point estimates from the industry-level regression is equivalent to the prefecture-level regression. More importantly, the two approaches provide similar statistically inference – the effects of *PollExShock* remains statistically significant at the 1% level. We take the above check as reassuring that the spatial correlation of residuals due to similar industrial composition is unlikely to bias the standard errors in our baseline analysis.

F.6 Initial Size of the Agricultural Sector/Tradable Sector

One may concern that there could be differential pre-determined trends in IMR in the initially agricultural regions. Our baseline specification controls for the initial agricultural employment share, which partly accounts for the pre-trends and/or other omitted variables that are correlated with the initial size of the agricultural sector. Column (1) of Table A.11 addresses this concern in a more non-parametric way by including quintile dummy variables for the initial agricultural employment share. The results remain stable. This finding, together with a variety of extensions and sensitivity checks regarding pre-trends discussed above, suggests that our baseline findings are unlikely to be driven by initial size of the agricultural sector.

For our baseline measures, the shocks to the non-traded sectors are set to zero. Therefore, a part of variation arises from the importance of tradable sector for local employment. We take two approaches to to alleviate the concern that our baseline findings are confounded by the initial size of the tradable sector. First, in column (2) of Table A.11, we control for quintile dummy variables for the initial employment share of the tradable sector. The estimates resembles the baseline findings. Second, in column (3), we reconstruct the Bartik measures using the employment shares within the traded sector as weights, and find consistent results.

[68]For the industry-level analysis, we first residualize the prefecture-level IMR and treatments (i.e., PollExShock and ExShock) by projecting these variables on the controls listed in column (7) of Table 3. To obtain the industry level IMR, PollExShock and ExShock, we then aggregate the residuals to the industry level based on $\frac{w_{it}s_{ikt}}{\frac{1}{N}\sum_{i=1}^{N} w_{it}s_{ikt}}$, where w_{it} represents the weights for prefecture-level regression, i.e., population of age 0 at the start-of-period. For the industry-level regression, the instruments for the treatments are $\gamma_t^p \frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$ and $\frac{\Delta \hat{X}_{CRkt}}{L_{ck,t-1}}$. In this exercise, we consider TSP pollution shock. Results remain similar for SO2 or NO2 pollution shock. As a related note, we may construct industry-level measures using the weighting scheme $\frac{s_{ikt}}{\frac{1}{N}\sum_{i=1}^{N} s_{ikt}}$, and the regression result is equivalent to that of the *unweighted* prefecture-level regression. The results as followed remain similar.

F.7 Reduction in Trade Policy Uncertainty

China was granted permanent normal trade relation (PNTR) status by the US upon its accession to the WTO, which reduces the trade policy uncertainty faced by Chinese exporters. Existing studies find that this exogenous shock has an significant impact on China's labor market (Erten and Leight, 2019; Facchini et al., 2019). In our baseline analysis, we adopt changes in tariffs faced by Chinese exporters instead of the reduction of trade policy uncertainty as the exogenous export demand shocks for two reasons. First, the sample period of our paper spans from 1992 to 2010. While the PNTR granted by the US provides useful exogenous variation for the second decade (2000-2010), it lacks power to explain the export expansion in the first decade (1992-2000). Second, the external tariff changes allows us to isolate the export demand shocks from the ROW instead from the US alone.[69]

If we restrict our analysis to the 2000s, the goal of isolating the exogenous variation in exports can be achieved by exploiting different exogenous demand shifters – either they come from actual tariff changes or uncertainty in trade policies. In this appendix, we use the NTR tariff gap to generate exogenous export demand shocks. If both the external tariff and the NTR gap are valid instruments for export flows, our results should be robust to different IV approaches. We use the NTR gap and corroborate the baseline findings by two steps. First, we compare the power of the external tariff and the NTR gap in explaining export flows at the industry level in Table A.12. Second, we demonstrate that our results are robust to alternative instrument formulations in Table A.13.

Column (1) of Table A.12 estimates the following model:

$$\Delta \ln Export_{kt} = \alpha + \theta \Delta \ln(1 + ExTariff_{kt}) + \varepsilon_{kt}, \tag{21}$$

where $\Delta \ln Export_{kt}$ and $\Delta \ln(1 + ExTariff_{kt})$ denote the changes in export and external tariffs (in logs) of industry k during the period 2000 to 2010. The estimated coefficient implies a trade elasticity of 7.8, which resembles the baseline estimate in Figure 3 of the main text. We then follow Pierce and Schott (2016) and Handley and Nuno (2016), and relate the export flows to the NTR gap (a proxy for the reduction in trade policy uncertainty):

$$\ln Export_{kt} = \psi_k + \delta_t + \gamma \mathbf{1}(t = 2010) \times NTR\ Gap_k + \varepsilon_{kt} \tag{22}$$

where $NTR\ Gap_k = \ln(1 + NonNTR\ Tariff_k) - \ln(1 + NTR\ Tariff_k)$.[70] ψ_k and δ_t denote industry and year fixed effects, respectively. The coefficient γ captures the effect of the reduction in trade policy uncertainty on export growth. For the ease of comparison with model (21), we

[69] The US share in Chinese total export is 20.9% in 2000.

[70] The data on NTR and non-NTR tariffs are obtained from Pierce and Schott (2016). We aggregate the the HS 8-digit product level tariffs to the 4-digit ISIC industries using the US imports from China in 2000 as weights. (The data on US imports at the 8-digit HS level are obtained from the US Census Bureau.)

estimate equation (22) using the first-difference model:

$$\Delta \ln Export_{kt} = \delta + \gamma NTR\ Gap_k + \varepsilon_{kt}. \tag{23}$$

Consistent with findings in the existing literature, industries with a higher NTR gap experienced a faster export growth during the decade. More importantly, the R-squared from model (3) is slightly lower than that of model (1). The finding implies that NTR gap *does not* outperform external tariffs in terms of its strength as an instrument. In column (3), we conduct a horse-race between the external tariff and NTR gap. The estimated coefficients remain statistically similar to those in columns (1) and (2). In terms of magnitude, we find that a standard deviation decline in external tariff induces export to grow by 0.35 log point, while a standard deviation increase in NTR gap raises export by 0.26 log point.

Having established the link between export and NTR gap, we construct alternative instruments as equations (8) and (9) in the main text, but replace $\Delta\hat{X}_{kt}$ by the changes in exports predicted by the reduction in trade policy uncertainty. More specifically, we obtain the exponential of the fitted value from equation (22), $\hat{X}_{kt} = exp(\hat{\psi}_k + \hat{\delta}_t + \hat{\gamma}\mathbf{1}(t = 2010) \times NTR\ Gap_k)$ and derive the decadal difference $\Delta\hat{X}_{kt}$.

In Table A.13, we restrict the analysis to the 2000s and check robustness with respect to different ways of formulate instruments. Column (1) adopts the baseline IVs constructed from external tariffs (as discussed in section 3.2), while column (2) uses the alternative IVs constructed from the NTR gap. Reassuring, we find the estimates are statistically similar. In column (3), we adopt atheoretical instruments as follows:

$$\widehat{PollExShock}^p_{it} = \sum_k \gamma^p_{kt} \frac{L_{ik,t-1}}{L_{i,t-1}} NTR\ Gap_k \quad \text{and} \quad \widehat{ExShock}_{it} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} NTR\ Gap_k.$$

Again, the IV estimates remain robust while the first stage results are weaker.

F.8 Changes in Other Trade Policies

In this appendix, we assess the likelihood that our estimates are severely biased due the omission of other trade policy shocks associated with China's accession to the WTO.

Direct trading right. As is shown in Bai et al. (2017), the removal of the restrictions on direct export promoted trade. It is important to note that before 2000, direct trading rights were granted to firms based on whether registered capital, revenue, net assets, and exports exceeded threshold levels. Such restrictions were gradually relaxed over 2000-2004. However, there is little cross-industry variation in the intensity of these restrictions and the timing of their removal.[71] Therefore,

[71] Mechanical and Electronic Products is the only sector that was subject to a lower threshold. For more details, please refer to the appendix of Bai et al. (2017).

this policy experiment is not ideal for our current approach to identify the effects of export shocks. (Recall that our identification strategy relies on the cross-industry variation in export expansion.) In fact, to the extent that the removal of direct export right affects industries similarly, its pollution effect on mortality and pollution will be captured by coefficients on $PollEmpl$. (See equation (5) in the main text.)[72] As is discussed in appendix F.3, our results remain stable when the sector "Mechanical and Electronic Products" is dropped from the analysis.

Export licence. A related trade barrier is export licence, which was imposed on a set of products in the pre-WTO period. According to the 2001 WTO report, 216 6-digit HS products were subject export licence. For the purpose of our analysis, we aggregate the product-level information and derive the coverage ratio of export license at the 4-digit industry level. In columns (4) and (5) of Table A.12, we investigate whether the export grows faster in industries that were more constrained by export license requirement in the pre-WTO period. The estimated coefficient is positive, but statistically insignificant. Moreover, the R-squared in column (4) is much smaller than those in columns (1) and (2). Given these findings, we decided not to purse an IV approach based on the export restrictions. Moreover, the correlation of coverage ratio of export license and $\Delta \ln(1 + ExTariff_{kt-1})$ is -0.08 and statistically insignificant. Therefore, our baseline results are unlikely to be biased by such export restrictions.

Quota removal under the Multi-fiber Agreement (MFA). The MFA only have impacts on the textile sector, although there is substantial variation in changes in quota at the product level within the sector. Due to the data constraint, we have to construct the pollution and export shocks at the industry level, but there are only 11 industries in the textile sector.[73] Moreover, the variation in pollution intensity within the textile sector is smaller than the variation across all industries.[74] Therefore, at the prefecture level, the MFA does not provide us enough statistical power to distinguish pollution effect from the income effect induced by export demand shocks. We show in Appendix F.2 that our results remain stable when the textile sector is dropped from the analysis. This finding alleviates the concern that due to the MFA, the textile sector is influential and drive our findings.

FDI liberalization. To alleviate the concern about the confounding effects from the concurrent FDI liberalization, we collect information on China's FDI regulations from the Catalogue for the Guidance of Foreign Investment Industries. We compare the last version before 2000 (i.e., 1997 version) and the last version before 2010 (i.e., 2007 version). In the Catalogue, products were classified into four categories: (i) products where FDI was supported, (ii) products where FDI was permitted (not listed in the Catalogue), (iii) products where FDI was restricted, and (iv) products

[72]If the change in export per worker ($\Delta X_{kt}/L_{k,t-1}$) induced by the removal of the restrictions on direct export is similar across industries, $PollExShock$ boils down $PollEmpl$ multiplied by a constant term.

[73]This constrain stems from the fact that our employment data are derived from the China Population Censuses, which is at the 3-digit CSIC level.

[74]For example, the coefficient of variation of emission intensity of TSP within the textile sector is 1.41. The coefficient of variation across all industries is 2.89.

where FDI was prohibited. We consider the FDI for a given product is liberalized if it was moved from the "restricted" or "prohibited" category to the "encouraged" or "permitted" category in 2007. Then, we aggregate the policy changes to the industry level. Specifically, $FDILiberalized_k$ is an indicator variable equals to one if there exists a liberalized product in industry k, and zero otherwise.[75] Column (6) of Table A.12 shows a positive but statistical insignificant effect of FDI liberalization on export growth. The R-squard is much lower compared to columns (1) and (2). Moreover, the correlation between $FDILiberalized_k$ and $\Delta \ln(1 + ExTariff_{kt})$ is -0.1 and statistically insignificant. Column (7) finds that estimated effects of external tariff and NTR gap are insensitive to the control of FDI liberalization.

We further assess the potential confounding effects of FDI by constructing pollution FDI shock and dollar value FDI shock at the prefecture level:

$$PollFDIShock^p_{it} = \sum_k \gamma^p_{kt} \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta FDI_{kt}}{L_{k,t-1}} \quad \text{and} \quad FDIShock_{it} = \sum_k \frac{L_{ik,t-1}}{L_{i,t-1}} \frac{\Delta FDI_{kt}}{L_{k,t-1}},$$

where ΔFDI_{kt} is the change in FDI stock of industry k during the period 2000 to 2007.[76] Analogous to pollution export shock, $PollFDIShock$ captures the pollution content of the FDI inflows. Column (6) of Table A.11 reports the robustness check with FDI shocks as controls. Pollution FDI shock tends to raise IMR, but the estimate is statistical insignificant. More importantly, the estimated effects of export shocks remain statistically similar to our baseline findings.

F.9 Robustness Checks: Effect of Export Shocks on Changes in $PM_{2.5}$ Concentration

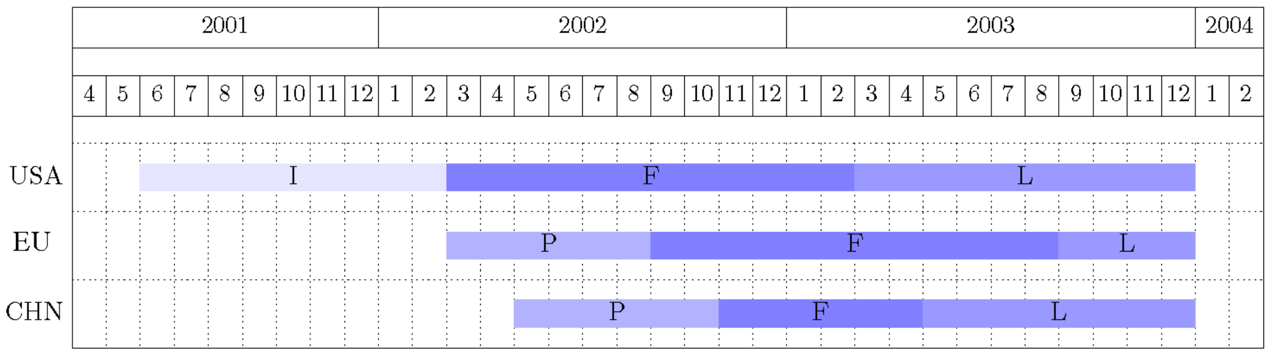
In this section, we establish the robustness of the relationship between export shocks and pollution concentration by repeating the robustness checks as discussed in Section4.3. We focus on pollutant $PM_{2.5}$ because, due to the data limitation, some of the robustness checks are restricted to the second decade (2000-10) for which we have more observations for $PM_{2.5}$ concentration. The results appear in Table A.14. Across all specifications, we obtain consistent findings as our baseline analysis.

[75] 22% of the industries experienced FDI liberalization over 1997 to 2007.

[76] Using the data from the Chinese Industrial Annual Surveys, we measure FDI stock by the equity from Hong Kong, Macau, Taiwan, and all other countries in the ROW. 2007 is the last year for which this information is reported.

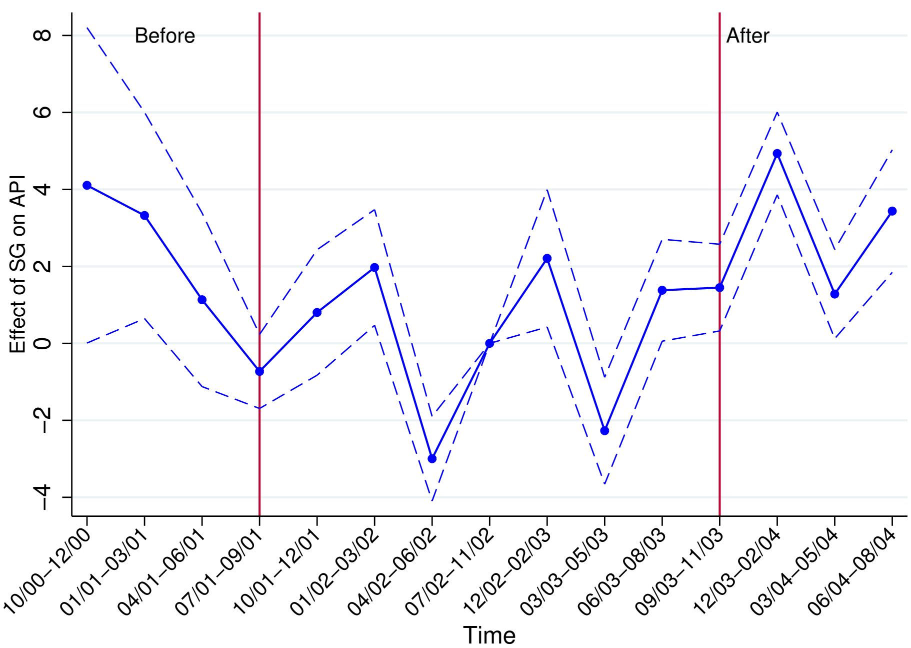
G Appendix Figures

Figure A.1: Timeline of Steel Safeguard



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

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



Note: This figure plots the estimates of and and the corresponding 95% confidence intervals of estimates of λ_τ from the following specification $API_{it} = \sum_\tau \lambda_\tau ShareSteel_i + \alpha_i + \phi_{ry} + \gamma_{rm} + \varepsilon_{it}$. The robust standard errors are clustered at the prefecture level. The red lines represent the start and the end of the steel safeguards.

Figure A.3: Initial Tariffs and Subsequent Tariff Changes

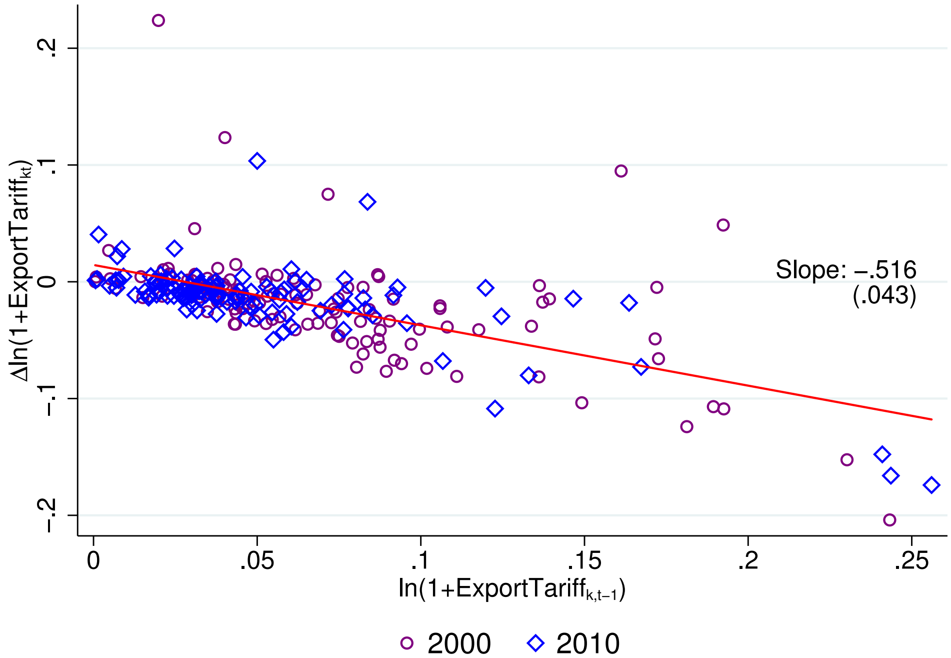


Figure A.4: Wind Direction Example

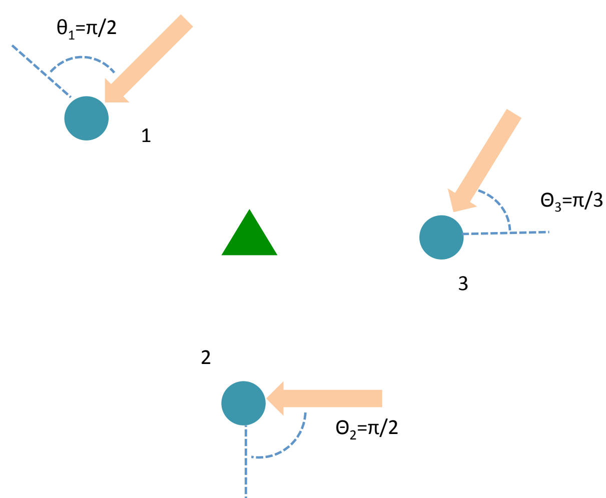


Figure A.5: Predicted and Actual Population Size of Age 10 in 2010

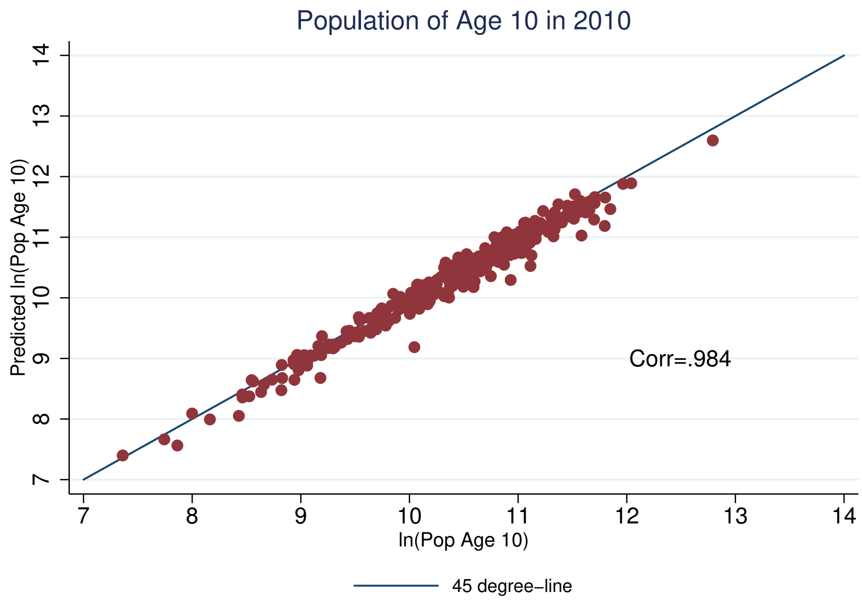
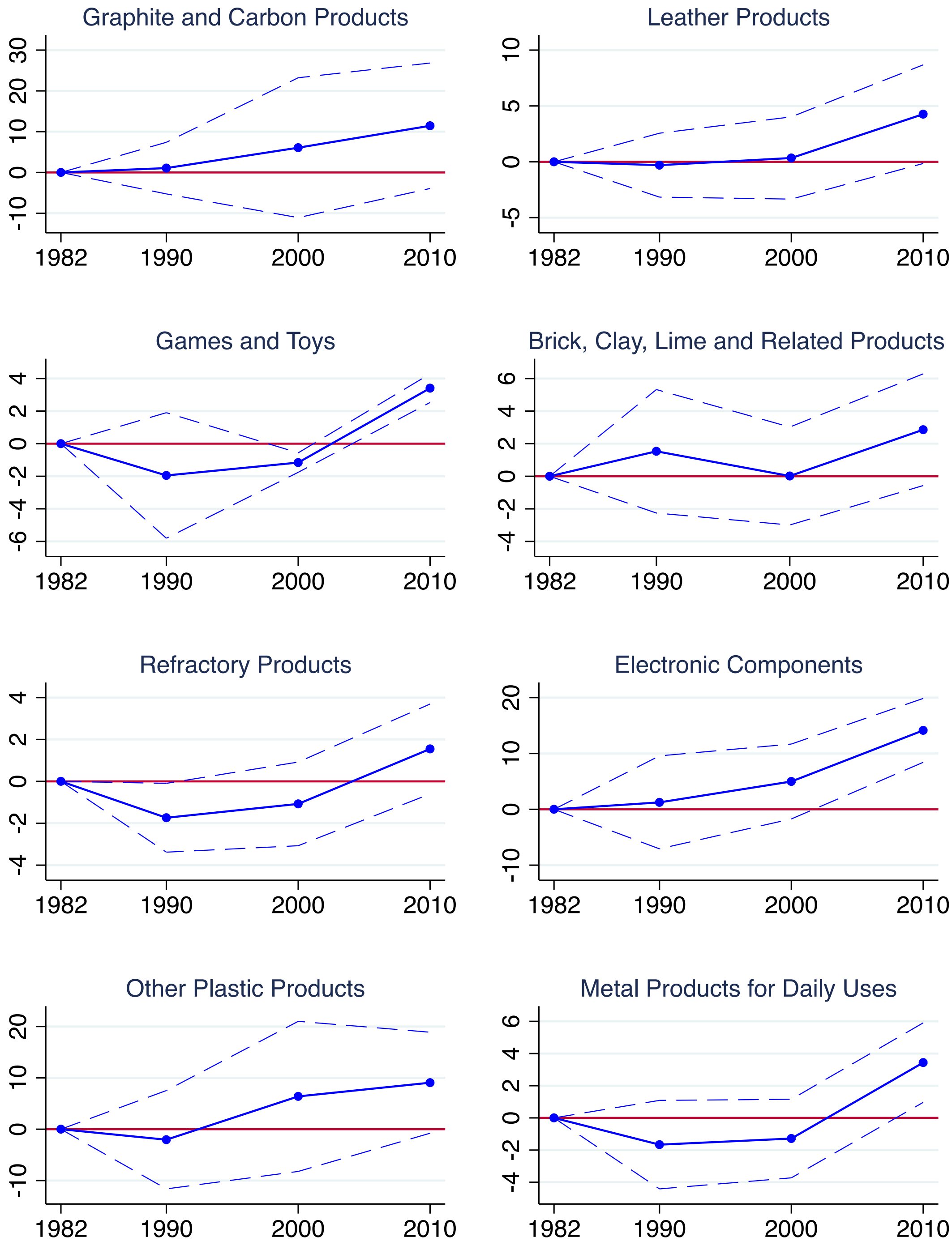


Figure A.6: Pre-trends for High Rotemberg Weight Industries



Notes: The figures fix industry shares at the 1990 values and report the effect of the industry shares on infant mortality. We run regression in changes in IMR and then convert to levels. The IMR in 1982 is normalized to 0, and the standard errors are calculated using the delta method.

H Appendix Tables

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

Dep. Var: API	(1)	(2)	(3)	(4)	(6)	(7)
$BeforeSG \times Share$	2.518**	2.592**				
	(1.059)	(1.048)				
$AfterSG \times Share$			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 A.2: Summary Statistics: External Tariffs and NTR Gap

	$\ln(1 + ExTariff_{kt})$		$\Delta \ln(1 + ExTariff_{kt})$		NTR Gap
	1992	2000	1992-2000	2000-2010	
Mean	0.071	0.051	-0.020	-0.015	0.252
Std	0.049	0.046	0.047	0.032	0.122
10^{th}	0.023	0.013	-0.070	-0.035	0.061
25^{th}	0.038	0.025	-0.038	-0.018	0.172
50^{th}	0.059	0.037	-0.015	-0.011	0.277
75^{th}	0.088	0.060	0.000	-0.003	0.312
90^{th}	0.139	0.096	0.007	0.004	0.384

The summary statistics are reported across 118 4-digit ISIC industries in the manufacturing sector. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: 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.4: 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.5: Monte Carlo Simulations

Parameter Values:	$\beta_1 = 2.5$ & $\beta_2 = 0$			$\beta_1 = 2.5$ & $\beta_2 = -1$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_1$	2.494	2.493		2.524	1.697	
	(0.392)	(0.238)		(0.403)	(0.260)	
$\hat{\beta}_2$	-0.001		1.851	-1.010		0.856
	(0.382)		(0.232)	(0.397)		(0.234)

Notes: The number of observations for each simulated dataset is 637. The table reports the average and the standard deviation of the estimates obtained from 500 simulated datasets.

Table A.6: Change in Infant Mortality Rate and Shocks: OLS

Dep. Var: ΔIMR	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PollExShock^{PCA}$	1.839***	1.609***			1.361**	2.371***	2.214***
	(0.228)	(0.512)			(0.505)	(0.612)	(0.639)
$ExShock$			1.191***	0.056	0.427	-0.938*	-0.841
			(0.317)	(0.527)	(0.365)	(0.499)	(0.522)
Region×Year	Y	Y	Y	Y	Y	Y	Y
Time-varying Controls		Y		Y		Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}		Y		Y		Y	Y
$PollEmpl^{PCA}$							Y
N	680	673	680	673	680	673	673
R2	0.342	0.628	0.339	0.623	0.342	0.631	0.631

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Influential Industries – Rotemberg Weights

Panel A: Top 5 Rotemberg Weight Industries

$PollExShock^{TSP}$		$ExShock$	
Industry	Weight	Industry	Weight
Graphite and Carbon Products	0.173	Games and Toys	0.280
Leather Products	0.130	Electronic Components	0.210
Games and Toys	0.086	Other Plastic Products	0.190
Brick, Clay, Lime and Related Products	0.085	Metal Products for Daily Uses	0.179
Refractory Products	0.072	Leather Products	0.140

Panel B: Top five Rotemberg weights as a share of positive weight

$PollExShock^{TSP}$	29.5%
$ExShock$	43.8%

Table A.8: Dropping One Sector or Two Sectors at a Time: 2SLS

Specifications:	Dropping one 2-digit sector		Dropping two 2-digit sectors	
Range of Estimates	min	max	min	max
	(1)	(2)	(3)	(4)
$PollExShock^{PCA}$	2.098***	2.613***	1.771***	2.743***
	(0.583)	(0.698)	(0.575)	(0.704)
$ExShock$	-0.860	-0.353	-1.129**	0.090
	(0.552)	(0.527)	(0.478)	(1.019)

Notes: All regressions includes the controls in column (7) of Table 3, observations are weighted by population of age 0, and standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Balance Checks

Independent Var.:	PollExShock		ExShock	
	coef.	t-stat	coef.	t-stat
	(1)	(2)	(3)	(4)
Dependent Var.:				
PollEmpl_{t-1}	0.079	(2.299)	0.089	(0.595)
Mortality Rate_{t-1}	0.074	(1.145)	-1.250	(-2.981)
Δ IMR_{t-1}	0.026	(1.036)	-0.618	(-2.793)
Population density_{t-1}	-0.243	(-1.455)	4.501	(2.983)
log GDP per capita_{t-1}	0.001	(0.024)	0.448	(2.805)
% Agricultural Share_{t-1}	-0.001	(-0.143)	-0.151	(-2.707)
Distance to the nearest port_{t-1}	0.006	(0.256)	-0.399	(-2.662)
Δ Hospital beds per capita_t	0.003	(1.310)	-0.007	(-0.424)
Δ Sex ratio_t	-0.000	(-0.293)	0.007	(1.307)
Δ % high school educated or above_t	0.000	(0.012)	0.014	(2.781)
Δ % middle school educated_t	0.000	(0.542)	-0.009	(-2.004)
Δ % Agricultural Share_t	-0.001	(-0.929)	0.016	(2.865)

Notes: This table reports coefficients from regressing industry-specific weighted averages of prefecture characteristics on industry shocks and year fixed effects. Standard errors are clustered at 3-digit CSIC codes. Regressions are weighted by average industry exposure. Coefficients are multiplied by 100 for readability. The sample includes 298 industry×period observations.

Table A.10: Location-Level v.s. Industry-Level Analysis: 2SLS

Specifications:	Local-Level	Industry-Level
	(1)	(2)
$PollExShock^{TSP}$	0.407***	0.407***
	(0.118)	(0.078)
$ExShock$	-0.291	-0.291
	(0.530)	(0.281)
Observations	673	298

Notes: Location-level regression in column (1) includes all the controls in column (7) of Table 3, observations are weighted by population of age 0, and standard errors are clustered at the province level. Industry-level regression in column (2) controls for period fixed effect, observations are weighted by average industry exposure, and standard errors are clustered at 3-digit CSIC codes. *** p<0.01, ** p<0.05, * p<0.1

Table A.11: Additional Robustness Checks: 2SLS

Dep. Var. ΔIMR	Quintile Dummies Agri Share (1)	Quintile Dummies Traded Share (2)	Within Traded Sector (3)	Controlling FDI Growth (4)
$PollExShock^{PCA}$	2.055***	1.941***	2.872***	1.554***
	(0.615)	(0.647)	(0.749)	(0.577)
$ExShock$	-0.638	-0.289	-0.365	-0.347
	(0.514)	(0.601)	(0.395)	(1.101)
$PollFDIShock$				2.142
				(1.494)
$FDIShock$				-13.133
				(9.304)
Region×Year	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y
N	673	673	673	340
R^2	0.630	0.635	0.626	0.746

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.12: External Tariffs, NTR Gap, Export License, and FDI Liberalization

Dep. Var.: $\Delta \ln Export_{kt}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \ln(1 + ExTariff_{kt})$	-7.359*		-8.775**		-8.829**		-8.723**
	(4.350)		(4.287)		(4.311)		(4.390)
$NTR\ Gap_k$		1.766*	2.167**		2.180**		2.149**
		(0.905)	(0.914)		(0.919)		(0.933)
$Export\ Licence_{k,2000}$				19.956	29.229		
				(38.689)	(26.112)		
$FDILiberalized_k$						0.191	0.029
						(0.180)	(0.175)
N	118	118	118	118	118	118	118
R^2	0.055	0.045	0.121	0.001	0.123	0.007	0.121

Notes: The analysis is conducted at the 4-digit ISIC level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.13: Change in Infant Mortality Rate and Shocks: Alternative Instruments

	(1)	(2)	(3)
	Panel A: 2SLS Estimates		
Dep. Var.: ΔIMR			
$PollExShock^{PCA}$	2.031***	1.716***	2.749*
	(0.531)	(0.645)	(1.441)
$ExShock$	-1.893***	-1.558***	-1.807***
	(0.447)	(0.479)	(0.512)
Angrist-Pischke F-statistics: PollExShock	46.17	51.43	8.992
Angrist-Pischke F-statistics: ExShock	122.1	136.5	37.76
	Panel B: First Stage Estimates		
Dep. Var.: $PollExShock^{PCA}$			
$\widehat{PollExShock}^{PCA}$	0.856***	0.582***	0.548***
	(0.116)	(0.108)	(0.114)
$\widehat{ExShock}$	-0.049	1.201***	2.254
	(0.062)	(0.376)	(5.638)
Dep. Var.: $ExShock$			
$\widehat{PollExShock}^{PCA}$	-0.148***	-0.416***	-0.445**
	(0.051)	(0.128)	(0.162)
$\widehat{ExShock}$	1.226***	4.121***	72.373***
	(0.111)	(0.697)	(8.780)
Region×Year	Y	Y	Y
Time-varying Controls	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y
N	340	340	340

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.14: Change in Pollution Concentration and Shocks: Alternative Specifications and Measures, 2SLS

Dep. Var: $\Delta PM2.5$	Prov ×Year Fixed Effects (2)	Unweighted Regression (2)	Without Normalization (3)	Neighboring Shocks (4)	Combined Local and Neighbors (5)	IO-adjusted Shocks (6)	Actual Export Expansion (7)	Export Share Weights (8)	Export Shock by Group (9)	Output Shocks (10)
$PollExShock^{PCA}$	1.078***	0.673*	0.141	0.840**	1.145	1.182**	3.475*	0.759***		
	(0.393)	(0.407)	(0.338)	(0.349)	(0.765)	(0.535)	(2.043)	(0.274)		
$ExShock$	-0.613	-0.733	-0.727	-0.758	-0.650	-0.267	-1.456	-0.525***		
	(0.684)	(0.523)	(0.638)	(0.470)	(0.476)	(0.336)	(1.096)	(0.186)		
$WindPollExShock^{PCA,N}$				0.570						
				(0.812)						
$ExShock^{N}$				-0.522						
				(0.657)						
$ExShock^{D}$									0.319	
									(1.286)	
$ExShock^{C}$									-0.964	
									(0.890)	
$PollOutputShock^{PCA}$										2.506**
										(1.005)
$OutputShock$										-0.233
										(0.185)
Region×Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	340	340	340	340	340	340	340	340	340	340

Notes: All regressions except column (2) are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table A.9 (Cont.) Change in Pollution Concentration and Shocks: Alternative Specifications and Measures, 2SLS

Dep. Var: ΔIMR	Energy Production (1)	Import Shocks (2)	High-skill Shock (3)	Share of Ownership (4)	TCZ (5)
$PollExShock^{PCA}$	0.959**	1.463	1.052***	1.003**	0.921**
	(0.421)	(0.938)	(0.408)	(0.416)	(0.432)
$ExShock$	-0.915	-1.684	-2.102	-0.998	-1.007
	(0.653)	(1.166)	(1.354)	(0.649)	(0.653)
$\Delta EnergyProd$	0.256***				
	(0.095)				
$PollImShock^{PCA}$		-0.629			
		(0.885)			
$HighSkillShock$			2.811		
			(2.591)		
$\Delta Share\ SOE$				-0.196	
				(2.503)	
$\Delta Share\ Foreign$				1.815	
				(4.021)	
TCZ					1.247
					(0.836)
Region×Year	Y	Y	Y	Y	Y
Time-varying Controls	Y	Y	Y	Y	Y
ΔIMR_{t-1} & ΔIMR^2_{t-1}	Y	Y	Y	Y	Y
$PollEmpl^{PCA}$	Y	Y	Y	Y	Y
N	340	340	340	340	340

Notes: All regressions are weighted by population of age 0. Time-varying controls include start-of-the-period GDP per capita, start-of-the-period overall mortality rate, start-of-the-period agriculture employment share, start-of-the-period population density, 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, and the interaction of year dummies with distance to the nearest port. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1