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中国社会科学院世界经济与政治研究所 经济发展研究中心 国际经济与战略研究中心

Working Paper No. 20.001

Jul. 3, 2020

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WTO accession, trade expansion, and air pollution: Evidence from China's county-level panel data[2]

Abstract

This study provides evidence that trade expansion has contributed to the degradation of air pollution in China. On the basis of different responses of counties' trade to China's World Trade Organization accession at the end of 2001, we exploit air pollution data from NASA to construct a difference-in-differences predicted trade as an instrument for our identification. We document statistically significant and robust evidence on trade expansion, which accounts for approximately 60% and 20% for the increase of $PM_{2.5}$ and SO_2, respectively, in China. Findings on trade pollution relation are robust to various tests. Deterioration in the environment is mainly driven by scale and trade in polluting sectors.

Key words: trade openness; air pollution; instrument variable; China

***JEL* Classification:** F18; F64; O13

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[2] This paper funded by National Natural Science Foundation of China, Grant/Award Number:71773148,71503281,71703149 and published in Wiley Online Library on 11 May 2020.

1. Introduction

A growing debate exists among academics and policymakers about how trade expansion affects the environment. However, scholars have not reached a consensus due to their heavy reliance on data from the developed world and data manipulation issue from the developing world.[3] In addition, the evidence of specific mechanisms is missing. This study uses China's, the largest developing country, data from NASA to fill the research gap, hoping to estimate a reliable impact about trade expansion on air pollution in the developing world.

In this study, we use Chinese county-level trade and NASA's air pollution concentration data, namely, average sulfur dioxide SO_2 ($\mu g/m^3$) and $PM_{2.5}$ ($\mu g/m^3$) concentration data. Trade expansion after World Trade Organization (WTO) accession accounts for approximately 60% and 20% for the increase of $PM_{2.5}$ and SO_2, respectively, in China. The rising trade-pollution effect is mainly caused by the size of high-pollution-intensive sectors, which are of first-order importance. Although pollution intensive trade structure contributes to pollution, it is improving over time.

In addition to reconciling seemingly contradictory results in the literature, we also provide detailed heterogeneities about the impact of trade expansion on air pollution in China. Moreover, the increasing effect of trade on air pollution is mainly driven by scale and pollution sector intensity, whereas the technology progress mitigate the impact of trade on air pollution and the pollution sector intensity is

[3] See Antweiler, Copeland, and Taylor (2001), Cole and Elliott (2003), Copeland and Taylor (2003, 2004), Frankel and Rose (2005), and Managi et al. (2009).

decreasing. These results can enrich our understanding about the impact of trade on pollution and indicate strong policy implications.

A main issue, often emphasized in the empirical literature, is that trade openness is endogenous in the regression. First, decisions on whether to trade and how much to trade are clearly not randomly assigned, wherein regions that trade more may be different from regions that trade less in ways related to the environment. Second, the regression analysis may be confounded by the feedback going from environment to trade openness, wherein traders can avoid polluted regions.

To address such issues, we rely on China's WTO accession as a natural experiment for identification. China is a classic example of a country that has undergone rapid development through trade policies. Given its accession into the WTO, China has grown from a small player in world trade to the world's largest exporter. At the regional level, China's accession into the WTO has affected some places more than others as regions differ in their degree of exposure to international trade because of geography. Coastal regions, for instance, have benefited most from the economic opportunities generated by China's accession into the WTO. Given that the WTO accession dramatically changed China's trade pattern by region and time, such an event has therefore been widely used in several previous studies (Han, Liu and Zhang, 2012; Lan and Li, 2015; Cosar and Fajgelbaum, 2016; Han, Liu, Ural Marchand and Zhang, 2016).

Using China's WTO accession as a subject for a quasi-natural experiment, we estimate the effects of trade openness on air pollution through a difference-in-differences (DID) and instrumental variable estimation strategy. First, we make use of two sources of sample variation to generate a predicted trade volume: (1) the difference of trade across counties after China's WTO accession and that of counties before 2001, and (2) the variation in trade between across counties. These variations enable us to compare the changes in the trade across counties before and after China's WTO accession in high-exposure versus low-exposure regions and thus estimate the effect of WTO accession on trade. Second, we use the WTO accession-induced trade as an instrument to run the two-stage-least squares (2SLS) estimation of the effect of trade on air pollution.

This study contributes to three streams of literature. First, our study contributes to the literature by providing evidence, which can be used to strengthen arguments on whether trade benefits or harms the environment. On the one hand, trade appears to be good for the environment from some cross-country analysis (e.g., Antweiler, Copeland, and Taylor, 2001; Copeland and Taylor, 2003; 2004, Frankel and Rose, 2005). These studies utilized data from developed countries. Given that high-income nations have higher trade and good environmental quality, the regression results often show that trade appears to be good for the environment. On the other hand, this observation may be overturned to the subset of less developed countries. Thus, we study the impact of trade on air pollution in the case of the world's largest developing country.

Second, we use WTO shock as a subject for quasi-natural experiment, which contributes to the literature utilizing WTO shock to study various topics. For example, China's trade expansion can increase income inequality (Han et al., 2012), productivity (Yu, 2015; Brandt, Van Biesebroeck, Wang and Zhang, 2017), firm mark-up (Lu and Yu, 2015), expand scope of exports (Feng, Li and Swenson, 2016), and provide better resource allocation (Khandelwal, Schott and Wei, 2013; Feng, Li and Swenson, 2017) and higher export quality (Fan, Li and Yeaple, 2015). However, China's trade expansion can also reduce education (Li, 2018) and innovation (Liu and Qiu, 2016). Unlike previous studies, this study is the first to look at whether trade expansion after WTO accession affects the environment by using China's county-level data.

Third, our study contributes to the debate on the relation between trade openness and environment in China.[4] Recently, China has been notable for its rapidly growing trade and serious environmental degradation. On the one hand, China is now the world's largest exporter; on the other hand, one-seventh of the country's territory is covered by $PM_{2.5}$.[5] However, Dean and Lovely (2010) found that China's trade has declined the pollution intensity. Similarly, de Sousa et al. (2015) found that trade in

4 Besides trade openness and air pollution, studies discussing the environment in China are numerous, for example, economic growth and environment (Lee and Oh, 2015), population growth and environment (Wang et al., 2015), and fiscal decentralization and environment (He, 2015).

5 Air pollution has become an issue associated with increasing social unrest, because it negatively affects our health (Chen et al., 2013; Bombardini and Li, 2016). Water pollution is also severe in China, drawing a lot of attention. For instance, Cai, Chen, and Gong (2016) and Kahn, Li, and Zhao (2015) investigated the political mechanisms behind river pollution. For instance, "Under the Dome," a 2015 self-financed, Chinese documentary film by Chai Jing who was a former China Central Television journalist, concerns air pollution in China, was viewed over 150 million times on Tencent within three days of its release on 28 February, 2015. This documentary was also reported by Financial Times, Forbes, BBC News, Financial Times, New York Times, and other international media.

China leads to lower pollution.

Thus, we need to look into the relationship between trade and air pollution in China carefully. Some studies used China's official pollution data; however, official data on the environment may be manipulated (Chen et al., 2012; Ghanem and Zhang, 2014). Manipulation decreases the quality and reliability of the official pollution data; thus, the use of such data can exhibit bias in the estimation. In this study, we use pollution data from the NASA.

The remaining parts of this study are structured as follows. Section 2 introduces our data. Section 3 presents the empirical strategy. Section 4 reports our results of trade openness on environment and robustness checks. Section 5 reports the heterogeneous effects and channel investigation. Finally, Section 6 concludes this study.

2. Data

Air pollution data: The air pollution data used in this article are monthly satellite-based retrievals. We obtain the satellite images from the product M2TMNXAER version 5.12.4 from the Modern-era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by NASA in the US[6]. The data has been reported at each 0.5 degree × 0.625 degree (approximately 50 km × 60 km) latitude by longitude grid every month since 1980. The concentration of SO_2 and AOD (aerosol optical depth) are reported in the raw data.

[6] The data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary.

The concentration of $PM_{2.5}$ is then derived from the satellite-based AOD retrievals. AOD essentially measures the amount of sunshine duration that are absorbed, reflected, and scattered by particles suspended in the air. Thus, AOD can be used to estimate particulate matter concentrations. In environmental science, the technique of AOD retrievals is popular for estimating $PM_{2.5}$ in areas lacking ground-level measurements (van Donkelaar et al., 2010). The concentration of $PM_{2.5}$ is calculated following the standard approach given by Buchard et al. (2016). The monthly pollution data are converted from grid to county by using the inverse-distance weighting (IDW) method,[7] wherein we take weighted average for all grids within the circle with a radius of 100 kilometers based on the centroid of each county. We then average such data to annual level across all months for each county during our research period. The AOD-based pollution data closely match the ground-based monitoring station measures (Gupta et al., 2006; Kumar et al., 2011).

Although previous studies showed that AOD-based pollution data can predict air quality (Gupta et al., 2006; Kumar et al., 2011), we compare our AOD-based data with ground-based data during the year 2013, when China National Environmental Monitoring Center (CNEMC) and the US Embassy started to report hourly concentration specific air pollutants; thus, manipulation is not a major concern.[8] We

[7] The IDW method is widely used in the literature to impute either pollution or weather data (Currie and Neidell, 2005; Deschênes and Greenstone, 2007; Schlenker and Walker, 2016). The basic algorithm takes the weighted average of all monitoring stations within a certain radius of the centroid of each county. We choose 100 km as our threshold radius. Our results are robust to different radii.

[8] For real-time air pollution data and the geographic locations of the eight monitoring stations, see http://www.cnemc.cn/ from CNEMC and http://www.stateair.net/web/historical/1/1.html from the US Embassy.

find no statistical difference between the two sets of data conditional on county-fixed effects. The details are discussed in the Online Appendix, Table A1.

We do not use air pollution data from ground-based monitoring stations for three reasons. First, the spatial coverage of publicly available data provided by the CNEMC of the Ministry of Environmental Protection of China was sparse. This data have covered only 42 cities in 2000 and 86 cities in 2010, whereas AOD-based data cover the whole country. Second, the ground-based pollution data have only reported Air Pollution Index (API), which is a piecewise linear transformation of three air pollutants (PM_{10}, SO_2, and NO_2). Thus, we cannot explore the effect of specific air pollutants, such as $PM_{2.5}$ and SO_2. Lastly, ground-based air pollution data have been manipulated (Chen et al., 2012; Ghanem and Zhang, 2014). We will also show in subsequent sections that all our baseline findings still hold when we use official API as alternative measurement for air pollution.

Table 1 shows descriptive statistics for $PM_{2.5}$ and SO_2. The average concentration of $PM_{2.5}$ from 2000 to 2013 is 60.25 ug/m^3, which is six times larger than the US EPA's standard. The average concentration of SO_2 during the same period is 18.36 ug/m^3, which is also considerably higher than that of most countries.

Table 1. Summary statistics

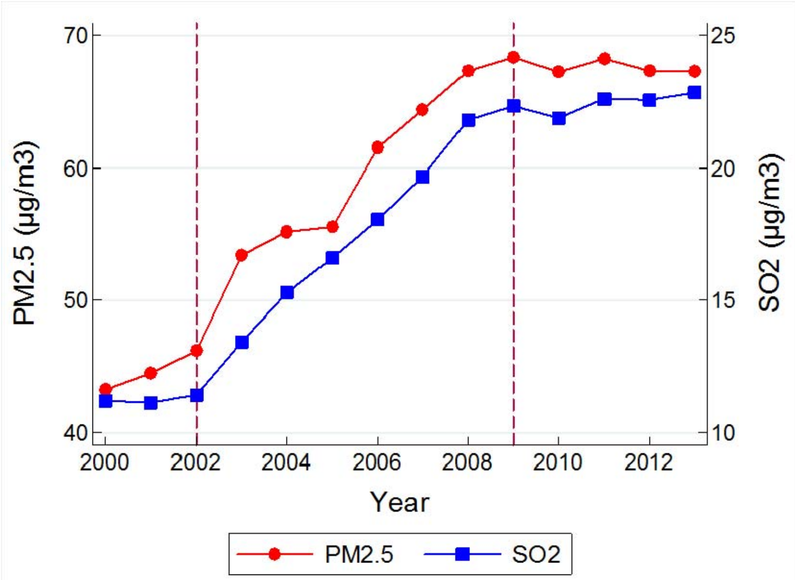
Variable	Definition (Unit)	Mean	SD	Min	Max
Air pollutant	*(μg/m^3)*				
$PM_{2.5}$	Particulate matter 2.5	60.252	31.133	3.17	157.597
SO_2	Sulfur dioxide	18.361	13.809	0.036	67.864
Foreign trade	*(billion $)*				
Trade	Foreign trade volume	3.003	9.411	0	249.498
Trade ratio	Trade/GDP×100% (percentage)	25.518	34.928	0	565.715

Export	Total export volume	1.751	5.124	0	95.805
Import	Total import volume	1.252	4.680	0	162.212
Intermediate-Import	Intermediate goods imports	0.462	1.696	0	55.187
Final-Import	Final goods import	0.305	1.322	0	50.824
Normal trade	Normal trade volume	1.757	5.050	0	145.390
Processing trade	Processing trade volume	1.245	5.349	0	148.277
Economic variables					
Log(TFP)	Total factor productivity	3.876	1.291	0.672	7.138
GDP per capita	GDP per capita (thousand $)	3.563	4.243	0.243	38.981
FDI ratio	FDI/GDP*100% (percentage)	2.197	2.779	0	45.400
Industry output	*(billion $)*				
IndustryOP	Total industry output	1.789	5.202	0	160.383
PollOP	Pollution intensive industry only	0.338	0.996	0	21.453
NonpollOP	Non-pollution intensive industry only	1.451	4.481	0	143.364

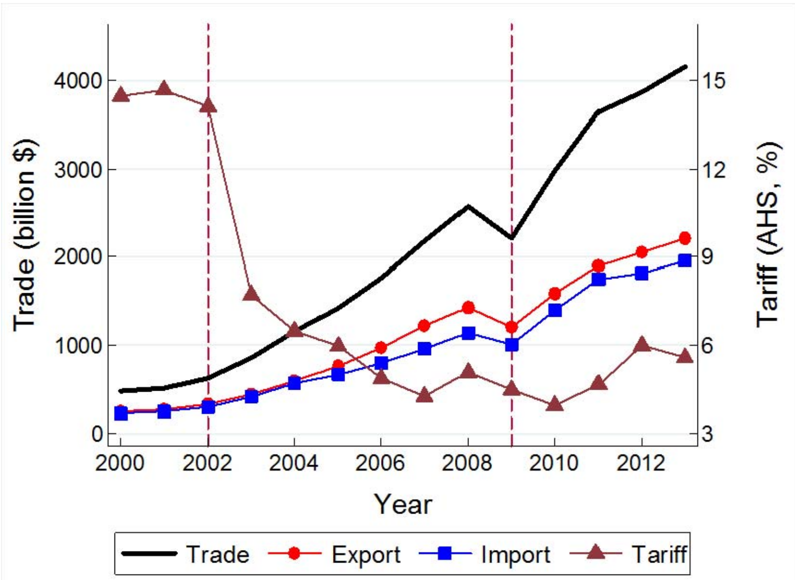
Notes: N=37,570; number of counties=2734; study period is from 2000 to 2013. Due to space limitation, we report summary statistics for weather controls in Table A2 in Appendix.

Trade data from Customs**:** Our main causal variable, county-level international trade (million US dollars), is obtained from China's General Administration of Customs. This government branch records a variety of information for each trading firm's product list, including trading price, quantity, and value at the HS eight-digit level. This rich data set includes import and export data and breaks down the data into several specific types of processing and ordinary trades. Such unique feature helps us investigate the heterogeneous effects later. We collapse the data to yearly frequency, aggregate at county level.

Panel (a) of Figure 1 draws the average national trend of $PM_{2.5}$ and SO_2 since 2000, whereas Panel (b) draws the national trade growth and tariff reduction trend. Trade has increased exceptionally fast after the WTO accession and declined during the financial crisis. Before joining the WTO, China has implemented tariff reductions and other trade policies to gain credibility among its negotiation partners. After joining the WTO, China further implements tariff rate reductions. As indicated in Panel (b), China's tariff fell sharply in 2001.



(a) Country average air pollution



(b) County total trade and tariff

Figure 1. Time trend of air pollution and international trade in China (2000-2013)

Notes: Panel (a) plots the county-average concentrations of $PM_{2.5}$ (μg/m^3) and SO_2 (μg/m^3) from 2000 to 2013, the course of our study period. Panel (b) plots the time trend of country-total, export, import, and trade volume (billion $), as well as the tariff measured by effectively applied tariff which is from http://wits.worldbank.org/wits/wits/witshelp/Content/Data_Retrieval/P/Intro/C2.Types_of_Tariffs.htm .

As shown in Figure 1, one stylized feature is that $PM_{2.5}$ and SO_2 increased significantly after China's WTO accession while and during the financial crisis when the trade bust took place. Air pollution in China seems to display a declining trend. The tight co-movement between trade and air pollution reveals their positive association.

We also divide trade into three parts, namely, intermediate imports, consumer imports, and exports for further heterogeneous effect investigation. Intermediate imports accounted for approximately 90% of China's imports, and in turn, fostered growth in processing trade, which is a significant component of the export of China, specifically, approximately 60% of exports over nearly 20 years (Fan et al., 2016; Dai et al., 2016). The database also records firm specific information such as custom regimes. We rely on two regimes: "ordinary trade" and "processing trade" for the heterogeneous effect investigation.

Mechanism data from the National Bureau of Statistics (NBS): Scale, pollution intensive structure, and TFP are obtained and estimated from a rich firm-level panel data set collected and maintained by China's NBS in an annual survey of manufacturing enterprises. Complete information on the three major accounting statements (i.e., balance sheet, profit and loss account, and cash flow statement) is available. In sum, the data set covers two types of manufacturing firms, namely, all state-owned enterprises (SOEs) and non-SOEs whose annual sales exceed RMB 5 million ($ 770,000).

The data set includes more than 100 financial variables listed in the main accounting statements of these firms. Although the data set contains rich information, some samples are affected by noise and are therefore misleading, largely because of misreporting by some firms. Following Cai and Liu (2009), we clean the sample and omit outliers by using the following criteria. First, observations with missing key financial variables (such as total assets, net value of fixed assets, sales, and gross value of firms' output productivity) are excluded. Second, firms with fewer than eight workers are omitted, given that they fall under a different legal regime, as mentioned by Brandt et al. (2012). Following Feenstra et al. (2014) and Yu (2015), observations are deleted according to the basic rules of the Generally Accepted Accounting Principles (GAAP). Specifically, observations are omitted if any of the following statements are true: (i) liquid assets are greater than total assets; (ii) total fixed assets are greater than total assets; (iii) the net value of fixed assets is greater than total assets, (iv) the firm's identification number is missing; or (v) an invalid established time exists (e.g., the opening month is later than December or earlier than January).

We use Cai et al.'s (2016) method to divide the sectors to high-pollution-intensive sectors on the basis of their industrial SO_2 emission intensity at two-digit industry level. The sectors with emission intensity above the median are classified as high-pollution sectors. We use high-pollution-intensive industrial output as the scale measure. Following Chen, Tian, and Yu (2019), we first estimate firm-level TFPs industry-by-industry. Then, we normalize them by using the national industry mean. Finally, we calculate the county-level mean TFP as the technique measure. We use the pollution intensive sector outputs share in total output as the structure composition measure.

Weather data from China Meteorological Data Sharing Service System (CMDSSS): Weather data are obtained from the CMDSSS, which records daily minimum, maximum, and average temperature, precipitation, sunshine duration, relative humidity, and wind speed for 820 weather stations in China.[9] We then average relative humidity and wind speed and aggregate precipitation and sunshine duration across days within each year and construct their second-order polynomials to capture the potentially nonlinear impact. For temperature, we followed the common practice in literature to count the number of days within each 5 °C temperature bin during the year to capture arbitrary nonlinear relationships (Deschênes and Greenstone, 2011; Chen et al., 2017). See Table A2 in the Appendix for the simple descriptive statistics for these weather variables.

Other data: Total GDP, income (real GDP per capita), and FDI share of GDP in each county is obtained from the China County Statistical Yearbook (various years).[10] Distance between county and coast is calculated by the Euclidian distance from the administrative center of a county to that of the nearest coastal county.

9 CMDSSS has been developed and is currently managed by the Climatic Data Center, National Meteorological Information Center, and China Meteorological Administration. See http://data.cma.cn/ for details.

10 These data can be downloaded at http://tongji.cnki.net/kns55/index.aspx.

3. Empirical strategy

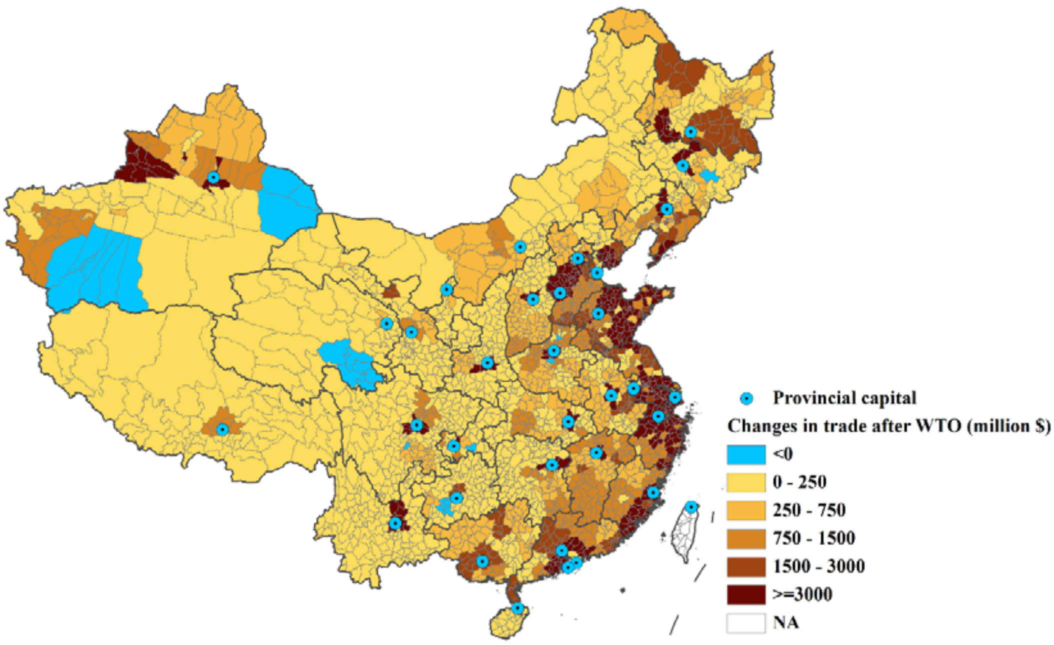
Our main estimating equation relates to $\log(\text{Air quality})$ and the log of year average SO_2 (ug/m^3) and $PM_{2.5}$ (ug/m^3) concentration data for county i at time t as:

$$log\ (Air\ pollution_{it}) = C_y + \beta log\ (Trade_{it}) + \delta Z_{it} + \sigma_i + \sigma_t + \vartheta_{it}, \quad (1)$$

where $log\ (Trade_{it})$ is our main causal variable, and C_y is the constant term. We let Z_{it} be the control variables that include county-level income and income square term, which are motivated by the *environmental Kuznets curve* (EKC) brought to public attention by Grossman and Krueger (1993, 1995), FDI with GDP ratio, and detailed weather controls including second-order polynomials in temperature, relative humidity, rainfall, sunshine duration, and wind force. σ_i is the county-fixed effects that control time invariant effect on air pollution. For example, geographic characteristics can affect pollution directly due to atmospheric dynamics. Coastal regions tend to receive more precipitation and stronger wind. σ_t is the year fixed effects that control macro or technology shocks to the economy by treating all cities identically. Finally, ϑ_{it} is the idiosyncratic error term clustered at county level.

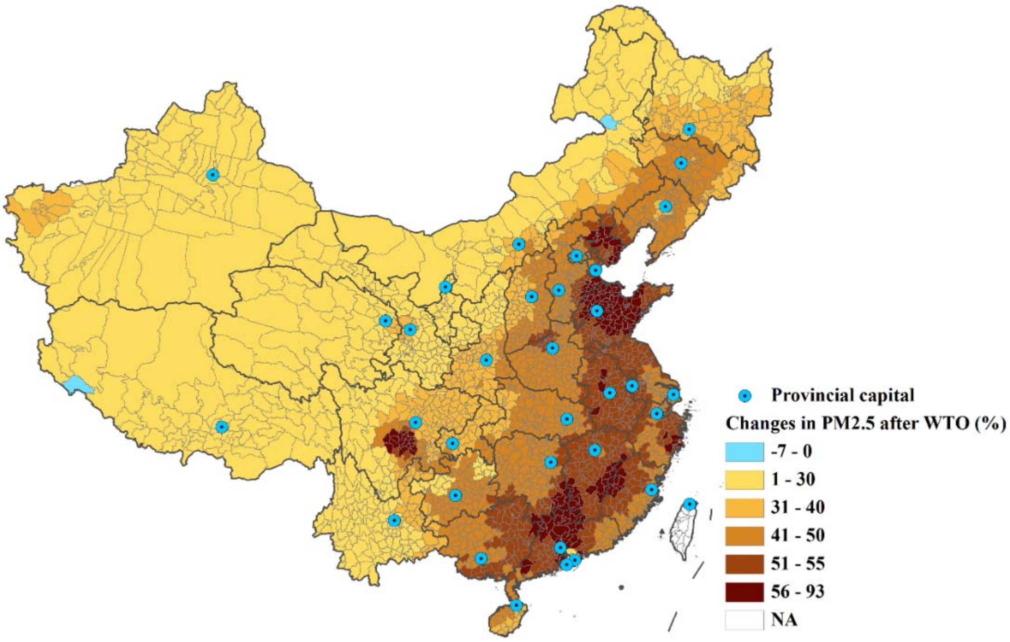
The summary of the extent of how trade affects air quality is provided by β, which is the elasticity of air pollution with respect to trade. However, such variable cannot be consistently estimated by OLS regression, given that trade is likely to be endogenous in the air pollution equation, in spite of controlling for county-specific characteristics and county- and year-fixed effects. First, other unobservable determinants of air pollution that are correlated with trade may be contained in the error term, such as regional environmental policy. Second, the unobserved potential air pollution may be correlated with trade. Thus, the OLS regression is susceptible to self-selection bias or reverse-causality problems.

This study uses WTO shock to obtain the exogenous variation in the trade and air pollution at the county level. To observe the implication of China's WTO accession on trade and air pollution, Panels (a) and (b) in Figure 2 illustrate in a graph the trade and air pollution increase for each county after WTO compared with pre-WTO era in the map of China. Eastern counties have a much higher value than inland regions in trade and air pollution. Similar with Figure 1, this co-movement pattern suggests at first blush the positive causal relation between trade and air pollution.[11]



(a) Changes in trade volume after WTO

[11] In addition to growth values, in the Appendix, Figure A1 shows the average trade and air pollution level values over our sample period of 2000–2013 for each county on the map of China, wherein regions with higher trade have higher pollution value.



(b) Changes in $PM_{2.5}$ after WTO

Figure 2. Changes in air pollution and international trade before and after WTO (2000-2013)

Notes: This figure depicts the changes in trade volume (Panel a) and $PM_{2.5}$ (Panel b) before and after WTO accessing by comparing the county-average values in 2000-2001 with the ones during the period 2002-2013. Number of counties=2734.

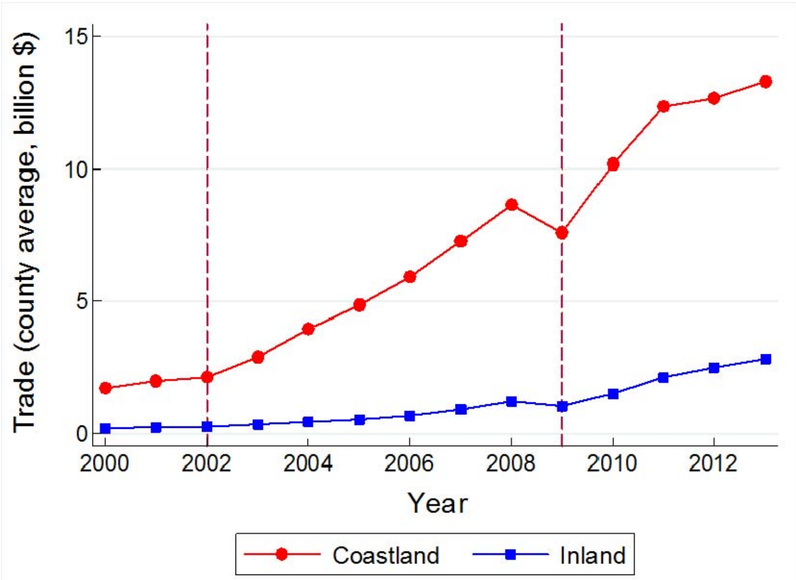
Figure 2 implies that China's WTO accession has varying effects on different regions, wherein eastern coastal areas have experienced a much greater increase in trade relative to what inland areas have experienced. Thus, we exploit the different responses of WTO access on high- and low-exposure counties to estimate the trade regression by using DID approach. On the one hand, China's WTO accession has led to a dramatic increase in the country's trade openness, which averagely corresponds to a 30% annual growth over the period of 2001–2007 (Figure 1). On the other hand, not all regions are affected in the same way, given that they have different degrees of exposure to trade due to geography (Figure 2).

In the literature (e.g., Han, Liu and Zhang, 2012; Lan and Li, 2015; Cosar and Fajgelbaum, 2016; Han, Liu, Ural Marchand and Zhang, 2016), Chinese regions are often classified into two categories on the basis of their geographical distance to the coast: regions with high-exposure to international trade versus regions with low-exposure to international trade.[12] Coastal regions that had more trade before 2001 are more likely to witness more increases in trade after China's WTO entry in 2001, given that they had gained more advantage in trade due to intra-national trade cost that separate firms and households from port or border (Atkin and Donaldson, 2015).

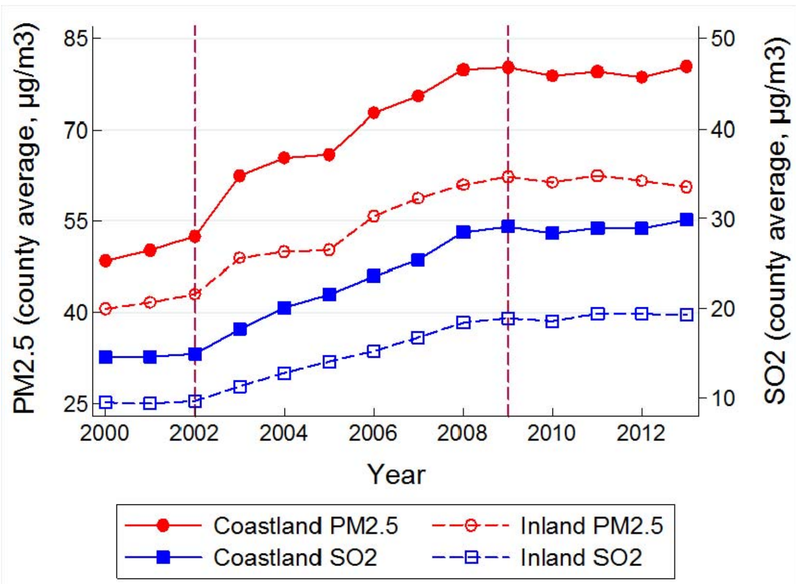
Following Han et al. (2012) and Lu and Yu (2015), we classify counties in 10 coastal provinces as high-exposure regions, including Liaoning, Beijing, Tianjin,

[12] This methodology is used to compare high-exposure and low-exposure regions before and after trade expansion shock. This methodology has been also used in previous studies for other developing countries, such as Goldberg and Pavcnik (2005) on Colombia, Hanson (2007) and Verhoogen (2008) on Mexico, Topalova (2010) on India, and Atkin and Donaldson (2015) on Ethiopia and Nigeria.

Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan, from north to south, and other counties in other provinces as low-exposure regions.



(a) County average trade (billion $)



(b) County average air pollutant

Figure 3. Time trend difference between the Coastland and the Inland (2000-2013)

Notes: This figure compares the difference in time trend of trade volume (Panel a) and air pollutant concentration (Panel b) between the coastland counties and the inland counties. Number of coastland counties=949; number of inland counties=1785.

Panel (a) of Figure 3 shows the simple average statistics about trade growth trend before and after 2001 (the year of accession) for high-exposure coastal regions (the treated group) and low-exposure inland regions (the control group). For the two groups, trade growth rate has a weakly parallel pretreatment trend before 2001. When we extend the time to 1980s in the Appendix Figure A2, we can find the parallel pretreatment trend over the period of 1980–2001. However, from 2001 onwards, such trend rises remarkably for coastal counties, whereas that of the inland provinces rises slowly. The estimating equation that relates the log of trade to the WTO shock is given by the following DID regression.

$$log\ (Trade_{it}) = C_y + \beta Coast_i \times WTO_t + \delta Z_{it} + \sigma_i + \sigma_t + \vartheta_{it}\ , \qquad (2)$$

where $Coast_i$ is the dummy variable that takes the value of 1 for counties that are located in coastal provinces and 0 otherwise. WTO_t is a dummy variable that denotes the post-WTO period and is equal to 1 for years 2002 and onwards and 0 otherwise. Later, we present further evidence in support of the common trend assumption regarding the effects of WTO accession on trade. We test formally whether the pre-trends for the two groups differ before 2001 by estimating more flexible regressions.

Specifically, we augment Equation (2) by replacing the treatment coastal dummy with a vector of year dummies. In doing so, we examine how the difference in trade outcome between high-exposure and low-exposure regions has varied over time. If a parallel pretreatment trend exists, then we should observe nonsignificant coefficient of the interaction term before 2002. However, if trade in high-exposure regions changes significantly after the WTO entry, then we expect to see the coefficient of the interaction term shifts significantly after 2001 (compared with before 2001). This formally tests the common trend assumption.

$$log\ (Trade_{it}) = C_y + \sum \beta_t Coast_i \times \sigma_t + \delta Z_{it} + \sigma_i + \sigma_t + \vartheta_{it}. \tag{3}$$

Equation (1) is estimated by using two-stage least squares in conjunction with Equation (2) as the first-stage regression. Panel (b) of Figure 3 also shows the simple statistics about the air pollution growth trend before and after 2001 for the high-exposure coastal and the low-exposure inland regions. Air pollution indices have a weakly parallel pretreatment trend before 2001. However, they rise remarkably for the coastal counties whereas that of inland areas rises much slower (Also see Appendix Figure A2). Thus, we also estimate the effect of WTO shock on air pollution by looking at the reduced form DID equation:

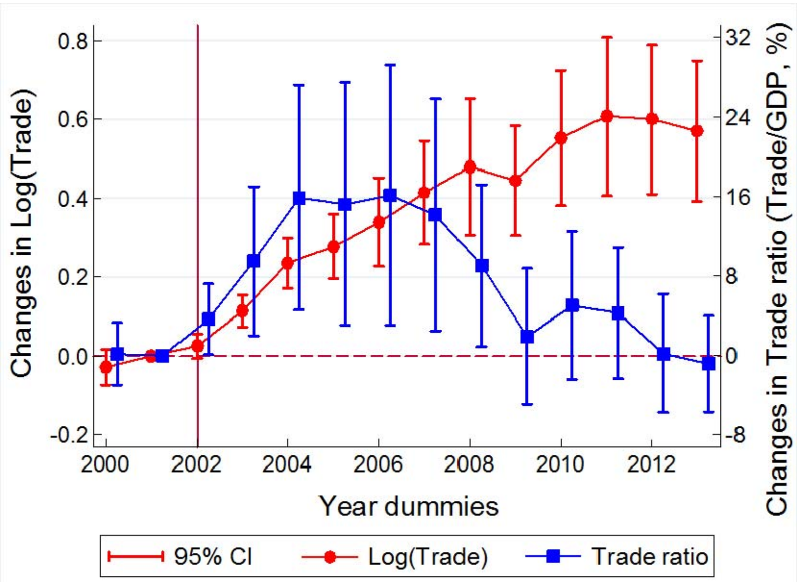
$$log\ (Air\ pollution_{it}) = C_y + \beta Coast_i \times WTO_t + \delta Z_{it} + \sigma_i + \sigma_t + \vartheta_{it}. \tag{4}$$

Equation (4) allows us to directly investigate the within-county effect that WTO accession has on air pollution, which is facilitated by the trade channel.

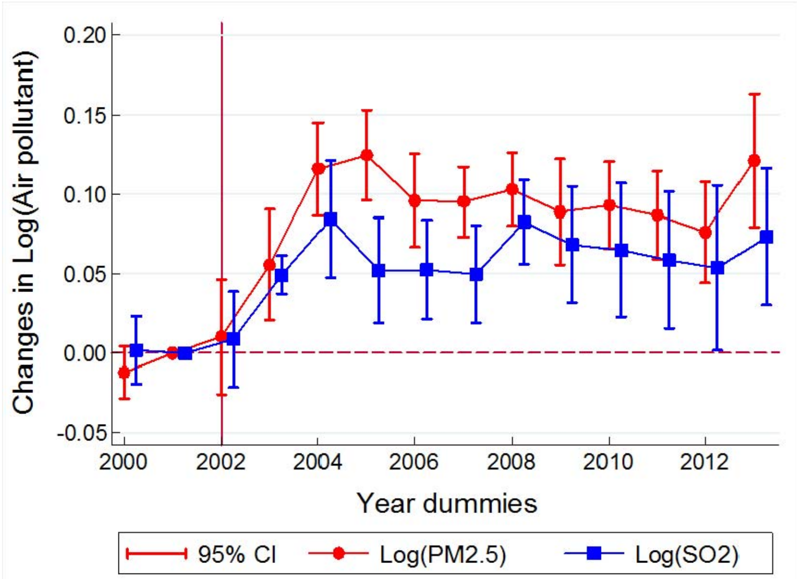
4. Results

4.1 DID-based instrumental regressions

Table 2 reports our baseline regression results by using the WTO shock as a natural experiment to gauge the trade effect on air pollution. Column (1) is the first stage results on trade by using DID approach. Before discussing the results, we first show the pre-trend analysis of our DID regression. The estimated coefficients of the flexible interaction term in Equation (3) and their 95% confidence intervals are plotted in Panel (a) of Figure 4, which show no significant differences in the trade growth and trade GDP share trend between high-exposure and low-exposure regions prior to 2001. However, since the 2001 WTO entry, a significantly positive effect in trade exists between high-exposure and low-exposure regions. This finding formally tests the common trend assumption and also provides further evidence for the impact of trade on air pollution.



(a) Pre-trend test for trade



(b) Pre-trend test for air pollution

Figure 4. Pre-trend tests (2000-2013)

Notes: This figure depicts the pretend test results of trade volume and trade relative to GDP ratio in Panel (a), as well as air pollutants in Panel (b). We construct year dummies (2000-2013) interacted with coastland counties (=1, otherwise=0). We then estimate the effects of all these interactions on Log(Trade), Trade ratio, Log($PM_{2.5}$), and Log(SO_2), and exclude year 2000 interaction as the base group, so that each estimated coefficient is interpreted as the trend comparison to year 2000. The scatter denotes the point estimate and the whisker denotes the 95% confidence interval.

Concerning identification, the first stage results suggest that the instruments are powerful. The DID instruments are significant at the 1% level with Kleibergen–Paap (KP) *F*-statistics well above the rule-of-thumb threshold of 16.38 suggested by Kleibergen and Paap (2006) and Kleibergen and Schaffer (2007). Although Figure 1 shows that trade and WTO accession are positively associated, the first-stage result confirms that the WTO is a strong determinant of trade expansion. Quantitatively, the first stage results show that, conditional on a bunch of the economic, weather, geography and year effects, WTO accession significantly increases county level trade by 40.6%.

Table 2. Baseline results

	1st-stage DD	Reduced-DD	2nd-stage IV

Depdent Variable:	Log(Trade)	Log($PM_{2.5}$)	Log(SO_2)	Log($PM_{2.5}$)	Log(SO_2)
	(1)	(2)	(3)	(4)	(5)
WTO×Coast	0.3409***	0.0974***	0.0606***		
	(0.0125)	(0.0026)	(0.0035)		
Log(Trade)				0.2766***	0.1682***
				(0.0113)	(0.0117)
KP *F*-Statistics	739.4				
Year *FE*	Yes	Yes	Yes	Yes	Yes
County *FE*	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

Notes: *N*=37570; number of counties=2,734; sample period 2000-2013. Column (1) reports the DID estimates of WTO shock on Log(Trade), which is the 1st-stage of 2SLS, while Column (2) and (3) provide the reduced DID estimates to examine the direct WTO shock on air pollutants. Column (5) and (6) are the 2nd-stage estimates in which WTO×Coast serves as an IV for endogenous Log(Trade) to respectively identify the causal effects of foreign trade on $PM_{2.5}$ and SO_2. Economic controls include GDP per capita and its squared form, as well as the percent share of FDI in GDP. For brevity, they are not reported here (see appendix Table A3 for the full DID-IV estimates). Weather controls include every 5 ºC temperature bins, second polynomials in relative humidity, precipitation, sunshine duration, and wind force. Standard errors are clustered by 2734 counties and are listed in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Columns (2) and (3) display the reduced regression results of our DID estimates of WTO accession on air pollution directly. Given the DID framework, we show the pre-trend analysis by running the flexible regression equation. We also draw the coefficients, wherein their 95% confidence intervals are plotted in Panel (b) of Figure 4, which show no significant differences in the air pollution trend between high-exposure and low-exposure regions prior to 2001. When we extend the time period back to 1998 in Appendix Figure A3, a significant parallel pre-trend is observed between the two groups. However, since the 2001 WTO entry, a significantly positive effect in air pollution exists between high-exposure regions and low-exposure regions. Reduced regression shows that WTO accession significantly raises air pollution: for $PM_{2.5}$, 10.2 percentage points and for SO_2, 5.6 percentage points.

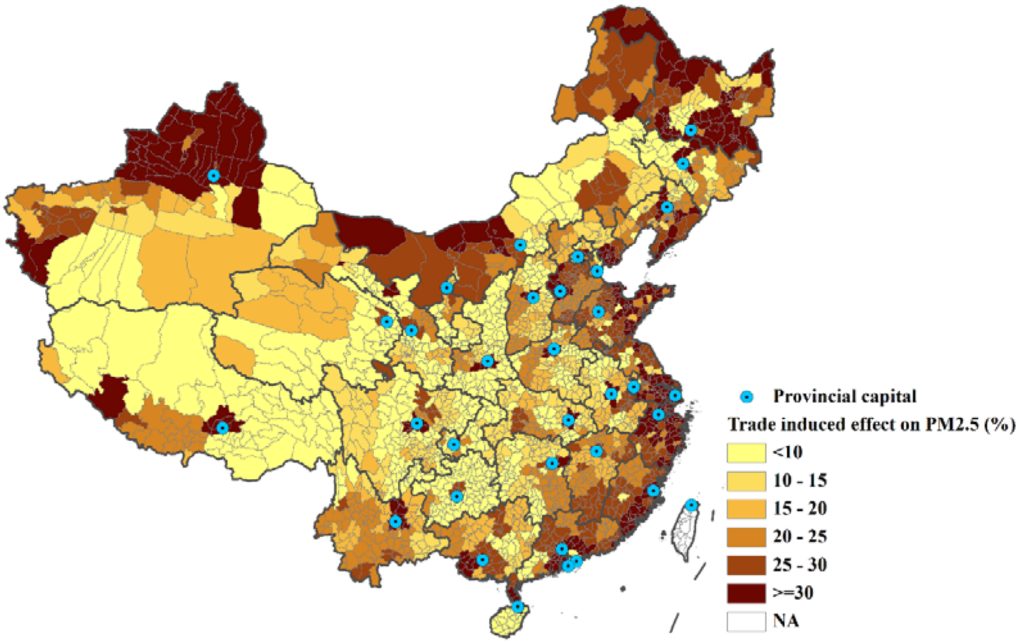
Columns (4) and (5) report the second-stage regression results of the elasticity of trade on air pollution, $PM_{2.5}$ and SO_2, respectively. Our findings demonstrate the importance of trade for the air pollution deterioration in China. The 2SLS estimates of the elasticity of air pollution with respect to trade for $PM_{2.5}$ and SO_2 are 0.277 and 0.168, respectively. A 1% expansion in trade raises $PM_{2.5}$ and SO_2 in China by approximately 0.28% and 0.17%, respectively, on average. Given that trade increases 86.43% after WTO, the increase of $PM_{2.5}$ and SO_2 should be 24.20% and 14.69%, respectively (86.43 × 0.28% and 86.43 × 0.17%). Given that $PM_{2.5}$ and SO_2 increase from 43.94 and 11.21 before WTO to 61.90 and 19.08 after WTO, the effect of trade on air pollution is 59.2% and 20.9% for $PM_{2.5}$ and SO_2, respectively.

One striking finding is that the trade accounts for a vastly significant proportion of the variation in air pollution. Given that trade and air pollution variations are county specific, we use to estimate the elasticity of trade with respect to air pollution. This process allows us to compute the county-specific explanatory power of trade on air pollution. For each county, Figure 5 plots the average effect of trade on air pollution using the following equation:

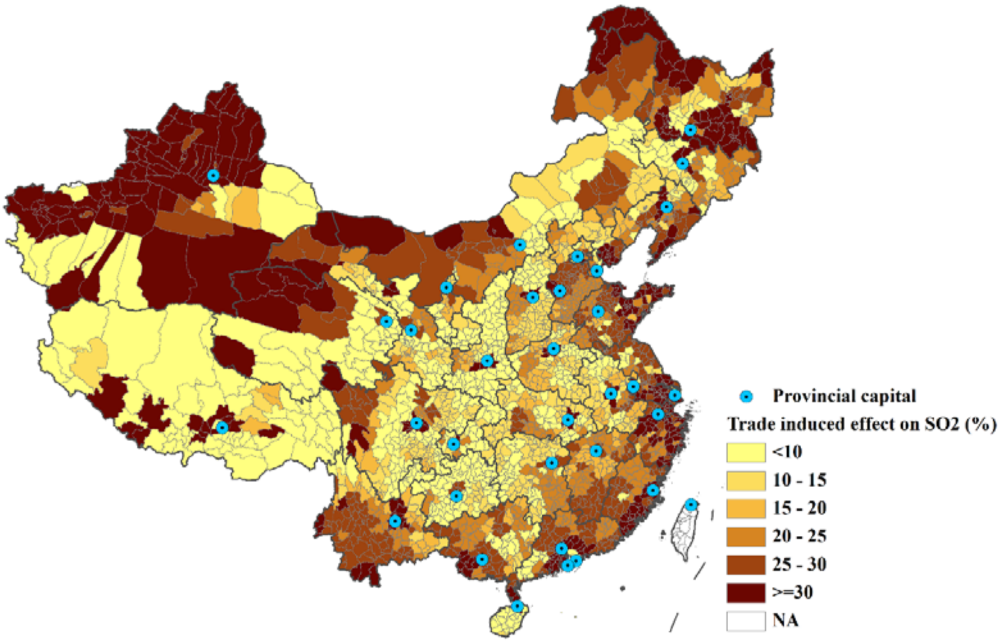
$$\frac{(\widehat{\text{Trade}}\times\beta)\times\text{Air pollution}_{\text{before WTO}}}{\text{Air }\widehat{\text{pollution}}}. \tag{5}$$

As Figure 5 shows, in eastern counties, trade-induced air pollution change accounts for a greater share of air pollution change. For example, in counties in Foshan Prefecture located in the southeastern coast of Guangdong Province, the average trade volume increased by 178.9% ($ 4,290 to $ 11,963 million) after the

WTO accession, which leads to nearly 49.5% (178.9% × 0.28) increase in $PM_{2.5}$ and 30.1% (178.9% × 0.17) increase in SO_2. The total changes in $PM_{2.5}$ (68.7 μg/m^3 to 107.2 μg/m^3) and SO_2 (34.4 μg/m^3 to 50.1 μg/m^3) before and after WTO is 55.9% and 45.7%, respectively. As a result, trade-induced effect on PM2.5 accounts for 88.6% relative to total changes in $PM_{2.5}$ (49.5/55.9 × 100%), whereas trade-induced effect on SO_2 accounts for 65.8% of total changes in SO_2 (30.1/45.7 × 100%).



(a) Trade induced $PM_{2.5}$/Total changes in $PM_{2.5}$×100%



(b) Trade induced SO_2/Total changes in $SO_2 \times 100\%$

Figure 5. Trade induced effect on air pollution after WTO

Notes: This map depicts the predicted trade induced effects on $PM_{2.5}$ (Panel a) and SO_2 (Panel b). Dark color indicates higher percent contribution to air pollution. The percentage is calculated by the ratio that trade induced air pollutant relative to total changes in air pollutant after WTO. Number of counties=2734.

These findings are consistent with the fact that trade and air pollution increases are higher in eastern areas than inland regions, as shown in Figure 2. However, for some western counties where air quality is good enough, the trade effect also shows a high value. Air pollution in these places change negligibly (see Figure 2 for reference), causing the denominator in Equation (5) to rarely change. For example, counties in Altay Prefecture located in Northeastern Xinjiang Province, the average trade volume increased by 42.8% ($ 291 to $ 415 million) after the WTO accession, which leads to nearly 11.8% (42.8% × 0.28) increase in $PM_{2.5}$ and 7.2% (42.8% × 0.17) increase in SO_2. The total changes in $PM_{2.5}$ (16.5 μg/m^3 to 18.8 μg/m^3) and SO_2 (1.2 μg/m^3 to 1.3

μg/m^3) before and after WTO is 14.3% and 8.9%, respectively. As a result, trade-induced effect on $PM_{2.5}$ accounts for 82.8% relative to total changes in $PM_{2.5}$ (11.8/14.3 × 100%), whereas trade-induced effect on SO_2 accounts for 80.9% of total changes in SO_2 (7.2/8.9 × 100%).

Control variables (in Appendix Table A3) show that with the increase in county-level income, air pollution also increases. However, when air pollution reaches a certain point, it will decrease given that the income square term shows a negative coefficient, namely, EKC introduced by Grossman and Krueger (1993, 1995). FDI seems to be good for SO_2 and shows a statistically nonsignificant effect on $PM_{2.5}$.

4.2 Bartik-type instruments and continuous treatments

The instrument used in this study is the interaction between the coastal and the post-WTO dummies. We provide evidence that, conditional on other control variables and covariates, the overtime trends of pollution are parallel across coastal and inland counties before 2001. This finding implies that the only reason why coastal counties differ from inland counties in pollution trends is because they have different exposures to trade due to coastal/inland geographic locations.

In spite of evidence, skeptical readers may argue that this finding seems a strong assumption, given that numerous factors may affect regional pollutions that are at the same time driven by coastal/inland location difference. If these factors cannot be effectively controlled in the estimation, then the regression suffers from omitted variable bias. For example, coastal regions are naturally more suitable for the building of ports and therefore more likely to become transportation hubs. Given that the transportation sector is more pollution-intensive, higher growth in pollution is more likely to be seen in coastal regions as trade and investment ties deepen. However, this difference in pollution growth is not entirely due to expansion in trade itself.

To address this concern, we rely on the initial industry specialization of a county to construct a "Bartik-type" trade exposure measure as the instrument, following Autor, Dorn, and Hanson (2013). If a county's industry structure is predetermined before the WTO accession and is persistent during the sample period, then the overtime change in trade exposure of a region can be relatively well predicted by its initial industry structure.[13] We compute the county-specific weighted average trade volume across different industries, using county-specific share of trade across industries in an initial year 2000 as weights. By doing so, a county initially specializing in China's fast-growing industries in trade is predicted to experience faster growth in overall trade after the WTO accession.

Column (1) of Table 3 reports the results using "Bartik-type" instruments in replace of the $Coast_i$ dummy variable in the above DID estimation. The positive and quantitative large impact of trade expansion on air pollution is evident. The coefficient of 0.22 for PM2.5 and 0.15 for SO_2 is close to the results in Table 2. In addition, as lower tariff rates mean a higher degree of openness, we also substitute WTO_t for the weighted average tariff rates Tariff_t as an alternative way to measure

[13] For example, if a county completely specializes in automobile production, and during the sample period China experiences fast growth in automobile trade, then we can expect this county itself to display fast growth in its overall trade as well.

trade expansion. In Column (2), the robustness of our results is shown by using "Bartik-type" instruments.

Moreover, instead of using "Bartik-type" instruments, we directly use the initial trade to replace $Coast_i$ dummy because similar with "Bartik-type" instruments idea, counties that had more trade openness before 2001 are more likely to witness an increase in trade openness after the WTO accession in 2001. Such counties have gained more advantage in trade in terms of information and relationship with foreign companies. We use the log of trade in each county before 2002 and the ratio of trade to GDP before 2002 for each county. We also use the geographical distance of each county to the nearest port to replace $\mathrm{Coast_i}$ given that counties in close proximity to the coast would be more likely to trade. We play with as many compositions of these interactions as possible, and all these robustness-check results are shown from Columns (3) to (8) of Table 3, which are very similar with our baseline regression results as copied in Table 2.

Table 3. Alternative trade shock definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade shock def.	WTO×Bartik	Tariff×Bartik	Log(Trade)$_{2000}$ ×WTO	Trade/GDP$_{2000}$ ×WTO	Trade/GDP$_{2000}$ ×Tariff	WTO ×Distance	Tariff ×Coast	Tariff ×Distance
Panel A: 1st-stage	*Dependent Variable* - Log(Trade)							
DID estimates	0.1598***	-0.0193***	0.1047***	0.0027***	-0.0003***	-0.0201***	-0.0422***	0.0024***
	(0.0373)	(0.0046)	(0.0376)	(0.0002)	(0.0000)	(0.0012)	(0.0015)	(0.0002)
KP *F*-Statistics	18.38	17.98	775.1	147.4	139.5	290.2	748.8	260.6
Panel B: 2nd-stage	*Dependent Variable* - Log(PM$_{2.5}$)							
Log(Trade)	0.2193***	0.2092***	0.3381***	0.3449***	0.3568***	0.6109***	0.2717***	0.6260***
	(0.0314)	(0.0350)	(0.0133)	(0.0248)	(0.0272)	(0.0306)	(0.0114)	(0.0333)
Panel C: 2nd-stage	*Dependent Variable* - Log(SO$_2$)							
Log(Trade)	0.1542***	0.1470***	0.1561***	0.1669***	0.1765***	0.6434***	0.1640***	0.6628***
	(0.0367)	(0.0385)	(0.0196)	(0.0213)	(0.0223)	(0.0387)	(0.0118)	(0.0414)

Notes: *N*=37570; number of counties=2,734; sample period is from 2000 to 2013. Strictly in line with our baseline regression in Table 2, all regressions in column (1)-(9) control year FE, county FE, economic variables, and weather controls. Robust standard errors are clustered by 2734 counties and are listed in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4.3 Further robustness checks

We continue to examine the robustness of the sign and statistical significance of the effect of $Coast_i \times WTO_t$ in our benchmark first stage, reduced regression results, and the elasticity of air pollution to trade. The first robustness check is related to the omission of other big events, which may affect our estimation. If other events happened at the same time, then any findings about the treatment effect cannot be attributed only to the effect of international trade. One important event regarding air pollution and trade is the global financial crisis after 2007 and other important fiscal policies during this unique period, such as the 4 trillion RMB investments, export tax rebates adjustment, and the fiscal subsidy policy about "home appliances going to the countryside." If the crisis affects coastal counties more strongly, then our aforementioned estimates of the effect of international trade could be contaminated.

For example, if during the financial crisis, more investments were put in coastal regions and pollution-intensive manufacturing sectors, then we would find similar positive estimated coefficients in Table 2 even without the effects of trade expansion. To address this concern, we use the subsample of the county-level data over the period of 2000–2007 to re-run the regression. Table 4, Column (2) reports the regression results. We find a much greater estimate in the first and second stage regression in this reduced sample, implying that our findings are not driven by the aftereffects of the global financial crisis in 2007.

Our second robustness check considers how sensitive our baseline results are to change the standard errors and temperature bins. Our benchmark regression clusters the standard error at county level, given that we use county-level trade variation for identification. We will now only use robust standard errors and cluster the errors at prefecture level to the robustness of the significance. Columns (3) and (4) report the results, and the same significance of our estimates is observed.

Our third robustness check looks into the robustness of our results when we change the measurement of our control variables. Given that Table A3 has already compared the results with and without economic variables and weather controls, in Column (5), we further examine more fine weather conditions. In practice, we extend our every 5 °C interval temperature bins to every 1 °C interval temperature bins, so that more flexibly nonlinear temperature effects are captured (see Table A2 for descriptive statistics about the weather variables). In summary, our baseline findings are not driven by additional or alternative controls.

Our fourth robustness check considers how sensitive our baseline results are to change the main causal variable. Our benchmark regression uses trade volume, and now we will use county-level trade over GDP share for identification. Column (6) reports the results. Quantitatively, our second stage estimation implies that a 1 percentage increase in trade share increases $PM_{2.5}$ and SO_2 by 1.15% and 0.71%, respectively. Given that trade share increases 15.98% after the WTO accession, the increase of $PM_{2.5}$ and SO_2 should be 18.38% and 11.35% (15.98 × 1.15% and 15.98 ×

0.71%), respectively. Given that $PM_{2.5}$ and SO_2 have increased from 43.94 and 11.21 before the WTO accession to 61.90 and 19.08 after WTO, the effect of trade on air pollution is 58.64% and 16.2% for $PM_{2.5}$ and SO_2, respectively. Thus, the effect is similar with our baseline regression using log of trade as the causal variable.

Although we stress that using the NASA data rather than the official data mitigates the data manipulation problem, determining if the results will change when the official pollution data is used to partly justify the claim will be interesting. Column (7) of Table 4 presents the results. The results remain positive, but the elasticity is small at approximately 0.07%, which is much smaller than the NASA data.

Table 4. Robustness checks

Scenario	Baseline	Period	Alternative clustering		1-Celsius	Alternative trade	Alternative pollution
		2000-2007	Robust	By prefecture	temperature bins	measurement	measurement
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 1st-stage	*Dependent Variable* - Log(Trade)					Trade ratio	Log(Trade)
WTO×Coast	0.3409***	0.2149***	0.3409***	0.3409***	0.3411***	8.4794***	0.3075***
	(0.0125)	(0.0079)	(0.0090)	(0.0360)	(0.0125)	(0.3765)	(0.0141)
1st-stage KP *F*-Statistics	739.4	740.2	144.2	89.37	739.4	506.6	473.9
Panel B: 2nd-stage	*Dependent Variable* - Log($PM_{2.5}$)						Log(API)
Log(Trade)/Trade ratio	0.2766***	0.4089***	0.2766***	0.2766***	0.2807***	0.0115***	0.0691***
	(0.0113)	(0.0172)	(0.0089)	(0.0314)	(0.0114)	(0.0006)	(0.0184)
Panel C: 2nd-stage	*Dependent Variable* - Log(SO_2)						
Log(Trade)/Trade ratio	0.1682***	0.2223***	0.1682***	0.1682***	0.1669***	0.0071***	
	(0.0117)	(0.0148)	(0.0087)	(0.0325)	(0.0117)	(0.0005)	
Observations	37,570	21,335	37,570	37,570	37,570	37,570	37,570
Number of counties	2,734	2,731	2,734	2,734	2,734	2,734	2,734

Notes: Sample period is from 2000 to 2013. In line with our baseline regression in Table 2, all regressions in column (1)-(7) control year FE, county FE, economic variables, and weather controls. The official API (air pollution index) used in column (7) is downloaded from CNEMC (http://www.cnemc.cn/). Robust standard errors are clustered by county and are listed in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

5. Heterogeneous effects and channel investigation

5.1 Export vs. import (intermediate and consumer imports)

Trade openness drives air pollution in China. An increase in trade expansion can be driven by either an increase in import or an increase in export. Given that in China's trade structure, exports are much larger than imports and imports are mainly intermediate goods for processing exports. Thus, China's trade increase is mainly driven by exports. To see whether exports or imports contribute more to air pollution, we use two causal variables to run the two-stage least square regressions using the products of log of exports and imports in each county before 2001 and post-WTO dummy variable as instruments.

Columns (1) and (2) of Table 5 report the results. Exports are mainly related to an increase in air pollution, approximately three and four times of the effect of imports on $PM_{2.5}$ and SO_2, respectively. We then decompose imports into intermediate imports and consumption goods on the basis of the BEC standard. Columns (3) and (4) demonstrate the regression results. Intermediate imports dominate the effect of imports on air pollution.

Table 5. Heterogeneous analysis

	Export and Import				Normal trade and Processing trade		Pollution and Non-pollution industry	
Dependent Variable	Log($PM_{2.5}$) (1)	Log(SO_2) (2)	Log($PM_{2.5}$) (3)	Log(SO_2) (4)	Log($PM_{2.5}$) (5)	Log(SO_2) (6)	Log($PM_{2.5}$) (7)	Log(SO_2) (8)
Log(Export)	0.2791***	0.2420***	0.3164***	0.1162***				
	(0.0235)	(0.0221)	(0.0198)	(0.0172)				
Log(Import)	0.0898***	0.0685***						
	(0.0266)	(0.0230)						
Log(Intermediate-Import)			0.0430***	0.0356***				
			(0.0058)	(0.0054)				
Log(Final-Import)			0.0291***	0.0048				
			(0.0054)	(0.0047)				
Log(Normal trade)					0.3249***	0.2274***		
					(0.0655)	(0.0544)		
Log(Processing trade)					0.2321***	0.1763***		
					(0.0615)	(0.0501)		
Log(PollOP)							0.2228***	0.1387***
							(0.0262)	(0.0176)
Log(NonpollOP)							0.0674***	0.0321**
							(0.0177)	(0.0144)
IVs	$Export_{2000\text{-}2001}$×WTO×Coast +$Import_{2000\text{-}2001}$×WTO×Coast		$Export_{2000\text{-}2001}$×WTO×Coast +$Media\text{-}Import_{2000\text{-}2001}$×WTO×Coast +$Final\text{-}Import_{2000\text{-}2001}$×WTO×Coast		$Normal_{2000\text{-}2001}$×WTO×Coast +$Processing_{2000\text{-}2001}$×WTO×Coast		$PollOP_{2000\text{-}2001}$×WTO×Coast +$NonpollOP_{2000\text{-}2001}$×WTO×Coast	
KP *F*-Statistics	76.96	76.96	108.41	108.41	28.79	28.79	113.5	113.5

Notes: *N*=36,847; number of counties=2,652; sample period is from 2000 to 2013. Strictly in line with our baseline regression in Table 2, all regressions in Column (1)-(4) control year FE, county FE, economic variables, and weather condition. Robust standard errors are clustered at county level and are listed in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

5.2 Processing vs. ordinary

We also investigate the heterogeneous effects of processing and ordinary trades on air pollution given that processing trade are shown to be a cleaner trade mode (de Sousa et al., 2015). We use processing and ordinary trades to run the regression by using the products of log of processing and ordinary trades in each county before 2001 and post-WTO dummy variable as two instruments. Columns (5) and (6) of Table 5 report the results. The results reveal that ordinary and processing trades contribute to air pollution significantly, although the effect of ordinary trade is slightly greater than processing trade.

5.3 Effects of pollution intensive industries

In this subsection, we will look into the effect of pollution-intensive sectors on trade–air pollution relationship. We define more polluting and less polluting sectors on the basis of the degree of SO_2 emission in each two-digit level sectors by treating the above median level sectors as polluting sectors and otherwise less-pollution sectors.[14] We aggregate the output from firm level data to the county level, and the firm-level data are from Annual Survey of Industrial Firms in China. This data set has been widely used in previous studies of the Chinese economy (e.g., Brandt et al., 2012; Fan et al., 2015b; Fan et al., 2015a; among others).

We use more and less polluting outputs to run the regression by using the

[14] For the official standard of polluting sectors, see http://www.gov.cn/xinwen/2018-02/06/5264316/files/27c5704a32e941e8ac20e40d61209a94.pdf.

products of log of more and less polluting outputs in each county before 2001 and post-WTO dummy variable as two instruments. Columns (7) and (8) of Table 5 report the results. The results convince that more-polluting sectors contribute to air pollution more than less-polluting sectors, approximately three and four times of the effect of less polluting sectors on $PM_{2.5}$ and SO_2, respectively.

5.4 Scale, technology, and composition effect

We study the channels of how trade affects air pollution using Antweiler, Copeland, and Taylor's (2001) framework. We use high-pollution-intensive industrial output as the scale measure. Following Chen, Tian, and Yu (2019), we first estimate firm-level TFPs industry-by-industry. Then, we normalize them by using the national industry mean. Finally, we calculate the county-level mean TFP as the technique measure. The pollution intensive sector outputs share in total output as the structure composition measure. We investigate the effect of scale, technology, and composition by adding them into the main regression:

Table 6 presents the results. Columns (1) and (5) add scale into the regression. The impact of trade on $PM_{2.5}$ and SO_2 decline to 0.096 from 0.28 and 0.17, respectively, implying that scale accounts for 65% and 44% of the effect of trade on $PM_{2.5}$ and SO_2. Scale itself drives air pollution. Columns (2) and (6) add trade structure into the regression. The results show that trade structure explains 33% and 18% of the effect of trade on $PM_{2.5}$ and SO_2, respectively. Pollution intensive trade structure itself also lifts air pollution.

Columns (3) and (7) only add TFP into the regression. Although it does not necessarily change the impact of trade on air pollution, technique itself seems to be good for air pollution. After we delve into three channel variables into the regression, Columns (4) and (8) show that the impact of trade on air pollution reaches zero. Thus, the results show that scale and trade structure dominate the effect of trade on air pollution, and scale alone has the greatest impact. As shown in Table 7, although trade significantly increases scale, trade actually increases productivity and improves composition, which is good news for future air quality.

Table 6. Mechanisms: scale, structure, and technique

Dependent Variable	Log($PM_{2.5}$)				Log(SO_2)			
	Scale	Structure	Technique	Total	Scale	Structure	Technique	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Trade)	0.0956***	0.1598***	0.2625***	0.018***	0.0957***	0.1391***	0.1449***	0.029***
	(0.0307)	(0.0113)	(0.0114)	(0.0305)	(0.0190)	(0.0113)	(0.0113)	(0.0193)
Log(IndustryOP)	0.0733***			0.0696***	0.0177***			0.0160***
	(0.0095)			(0.0093)	(0.0055)			(0.0054)
PollOP/IndustryOP		0.0186***		0.0159**		0.0284***		0.0278***
		(0.0063)		(0.0075)		(0.0077)		(0.0079)
Log(TFP)			-0.0041*	-0.0150***			-0.0081***	-0.0035*
			(0.0021)	(0.0037)			(0.0020)	(0.0025)
Observations	35,802	36,338	36,396	35,802	35,285	36,338	36,396	35,285
Number of counties	2,591	2,652	2,657	2,591	2,538	2,652	2,657	2,538
KP *F*-Statistics	33.59	673.3	672.8	33.94	34.09	673.3	672.8	33.95

Notes: Sample period 2000-2013. Strictly in line with our baseline regression in Table 2, all regressions in column (1)-(8) control year FE, county FE, economic variables, and weather condition. Robust standard errors are clustered by county and are listed in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Effects of trade on scale, structure, and technique

	(1)	(2)	(3)
Dependent Variable	Log(IndustryOP)	PollOP/IndustryOP	Log(TFP)
Log(Trade)	0.3484***	-0.0554**	0.038***
	(0.0860)	(0.0220)	(0.012)
Observations	36,338	36,338	34,490
Number of counties	2,652	2,652	2,597
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
KP *F*-Statistics	342.5	342.5	76.19

Notes: Sample period 2000-2013. Strictly in line with our baseline regression, we also use WTO×Coast as IV to instrument the endogenous Log(Trade), while the year FE, county FE, economic controls, and weather condition are also controlled. Standard errors are clustered by county and are listed in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

6. Conclusion

The existing literature provides inconclusive results on how trade causally affects the environment in China. In this study, we identify the effect of trade on the environment using new air quality measure from NASA rather than from China's official data. Some literature cautions that manipulation problem may exist with China's environmental data. Using China's WTO accession as a subject for a quasi-natural experiment, we estimate the effects of trade openness on air pollution through a DID and instrumental variable estimation strategy.

Using county-level panel data for the period of 2000–2013, we have found that trade appears to have a harmful effect on some measures of air quality, such as SO_2 and $PM_{2.5}$. Numerous robustness checks provide consistent evidence that trade has an overall detrimental effect in China, which complies with the hypothesis of an international race to the bottom driven by trade and the pollution haven hypothesis. Thus, we should be careful when expanding opening up by trying to avoid such pollution haven phenomenon.

Export and trade in pollution-intensive sectors dominate the impact of trade on air pollution. Ordinary and processing trades contribute to air pollution with similar effects. Intermediate imports show a greater effect on air pollution than imports of consumption goods. Evidence supporting the claim that scale and pollution intensity significantly magnifies the impact of trade on air pollution, whereas technique progress mitigates it is provided in this study. The good news is that the pollution intensity is improving and technology is also progressing, which may bring a bright future for China.

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