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Does export liberalization cause the agglomeration of pollution? Evidence from China☆

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ABSTRACT

This paper investigates the impact of export liberalization on the geographic concentration of water pollution. Data shows that water pollution emissions are unevenly distributed across regions in China. Using China's accession to the World Trade Organization (WTO) as the exogenous shock, we identify a negative causal effect of export liberalization on the agglomeration of water pollution across regions in China. It suggests that relatively more water pollution is discharged in those previously low-pollution regions after export liberalization. We confirm this with data on regional relative pollution emissions. Further decomposition shows that it is the intensive margin (average pollution emission) rather than the extensive margin (number of polluting firms) that drives the deglomeration of water pollution emissions within the liberalized industry.

1. Introduction

Many developing countries face the tradeoff between economic development and environment protection. In China, this tradeoff is more complicated given its geographical size and regional disparity. It is well-documented that economic development is uneven across regions. This is also true for pollution emissions given different industry structures and development levels. Additionally, environmental regulations are heterogeneously enforced across different regions in China.[1] Understanding the distribution of pollution emission is crucial for China's battle on pollution, as well as for the welfare across different regions.

Trade liberalization has been shown to promote economic development unevenly across regions. Its overall impact on pollution emission also has been studied quite well in the literature.[2] However, how it changes the geographical distribution of pollution emission in China is unclear. On the intensive margin, export-side trade liberalization may scale up the level of output as well as pollution emission disproportionately, leading to geographically more concentrated pollution distribution. It may also induce large

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[1] For instance, the five-year plans set different targets for different regions, see Fan, Graff, Zivin, Liu, and Wang (2019) for example. We also see anecdotal evidences that firms move from coastal regions with stricter environmental regulations to inland regions with weaker regulations. He, Wang, and Zhang (2020) have also highlighted the water pollution emission along the river due to local governments' selective regulation enforcement.

[2] See Copeland and Scott Taylor (2004) for a review, and Chen et al. (2021) on the case of water pollution in China.

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productive firms to adopt cleaner technology. This so-called "technique effect" may decrease pollution emission of larger firms, attenuating the geographical concentration of pollution emissions. On the extensive margin, there may be disproportionately more new entries or less exits in those *ex-ante* low-pollution (high-pollution) regions, attenuating (strengthening) the agglomeration of pollution emissions. We investigate the relationship between trade liberalization and the geographical distribution of pollution empirically using firm-level data from China, the largest developing country and exporter in the world.

China joined the World Trade Organization (WTO) at the end of 2001 and its total exports grew rapidly by 397.1% from 1999 to 2006. Plenty of studies have found a strong correlation between trade liberalization and pollution emission, for example, Bombardini and Li (2020) show that the prefecture-level export expansion has led to more local air pollution emission in China. However, these studies only show that export liberalization increases local pollution emissions. Its impact on the geographical distribution of pollution emissions is still unknown. Given the significant distributional impact of trade liberalization on regional economic development in China, it is also worth investigating whether there is such distributional impact of trade liberalization on pollution emissions across regions. Additionally, knowing the distribution of pollution may also help to design optimal policies for pollution control. For instance, as discussed by Forslid, Okubob, and Ulltveit-Moe (2018), if more productive firms (or regions) invest more intensively in abatement, then it is efficient to maintain certain level of pollution concentration (or agglomeration). Given the significant heterogeneity in the enforcement of environmental regulations across regions in China, the geographical distribution of pollution emissions is of utter importance for the success of China's national battle against pollution.

This paper fills the gap by investigating the geographic concentration of water pollution around China's WTO accession using data on water pollution emissions.[3] Water pollution has been strictly regulated since the 1980s in China. The Ministry of Ecology and Environment (formerly known as the Ministry of Environmental Protection) has tracked a record of firm-level pollution emissions, known as the *Annual Environmental Survey of Polluting Firms* (AESPF).[4] Together with other firm-level information collected by the National Bureau of Statistics (NBS) of China in the *Annual Survey of Industrial Firms* (ASIF), we are able to investigate the relationship between export liberalization and the geographic concentration of water pollution. We measure the geographic concentration of water pollution in each industry following Ellison and Glaeser (1997) where they provide an indicator for production or employment agglomeration by controlling for differences in the size distribution of plants and differences in the size of the geographic areas. Analogously, we construct our indices that control for differences in the size distribution of firms and differences in the size of geographic areas.

In order to identify the causal effect, we rely on the exogenous shock of export liberalization upon China's WTO accession. Though the applied tariff rates for Chinese exporters were already the most-favored-nation (MFN) rates and they did not decrease much after China's WTO accession, there was a significant change in terms of policy uncertainty regarding these export tariffs which mainly concerns to the export to the United States (US). This is because the normal trade relations (NTR) with China was subject to annual renewal by the US government before 2001. Chinese exporters would face a much higher tariff schedule, i.e. the non-MFN tariff rates, if NTR was not renewed. Given the significant difference between the two tariff schedules, this uncertainty significantly discouraged Chinese exporters. It was until the permanent normal trade relations (PNTR) between China and the US took effect upon China's accession to the WTO that this policy uncertainty was eliminated. A growing stream of studies have shown that this elimination of trade policy uncertainty (TPU) significantly boosted Chinese exports, e.g. Pierce and Schott (2016), Handley and Limão (2015, 2017), and Feng, Li, and Swenson (2017), not only to the US market, but also to the rest of the world.[5] Following this literature, we use the difference between the MFN tariffs and non-MFN tariffs to measure the pre-WTO TPU for each industry.[6] These pre-WTO TPU levels vary across industries and were all eliminated upon China's WTO accession. Hence the heterogeneous TPU reductions across industries upon WTO accession provide an ideal setting for us to apply a generalized difference-in-differences (DID) framework to identify the causal effect of industry-level export liberalization on the geographical concentration of pollution.[7]

Our DID estimation results reveal that water pollution in those industries with higher pre-WTO TPU levels, i.e. stronger export liberalization after the WTO accession, became less geographically agglomerated relative to other industries after China's WTO accession. It suggests that export liberalization in terms of TPU reduction significantly reduced the water pollution agglomeration in the liberalized industry. Based on our estimates the water pollution agglomeration index dropped by about 0.48, or 18.4% of the standard deviation for water pollution agglomeration indices, for industries with an average level pre-WTO TPU relative to industries with zero pre-WTO TPU upon China's WTO accession. This causal effect is robust to a number of industry-level control variables as well

[3] Our main results focus on water pollution emissions, though we also investigate other pollutants, the results are not statistically significant and robust. There can be many potential explanations. One is that water pollution is more generally seen in most industries compared to other types of pollutants. Hence, data on water pollution is more readily available for more industries. Note that our results should not be generalized without caution to other types of pollutants, as shown by Cole and Elliot (2003) and others that different pollutants might response differently to trade liberalization.

[4] Chemical oxygen demand (COD) is the common measure for water pollution emission. It refers to the amount of oxygen that can be consumed by reactions in a given volume of water to reflect water quality. Higher COD is associated with more pollutants in water. The AESPF provides this record for Chinese manufacturing firms.

[5] This pattern has been documented by Feng et al. (2017) among others. It can be easily rationalized when there is fixed cost for exporting regardless of destinations.

[6] There are other types of trade policy uncertainty related to anti-dumping threats or trade conflicts studied in the literature, for example by Crowley et al. (2018).

[7] Though we do not use the reductions of actual MFN export tariff rates to represent export liberalization, we include these tariff reductions as controls in all our empirical exercises. Refer to Section 2 for more discussions on our empirical strategy.

as a battery of robustness checks, including checks on the identifying assumptions of our DID estimation strategy, alternative measures for TPU and alternative regional levels in the construction of water pollution agglomeration indices. We also show that the deglomeration effect of export liberalization on the spatial distribution of water pollution is stronger for industries with lower capital intensities, lower average wage levels and higher pollution intensities. Additionally, the effect is also stronger for industries with more foreign firms or with larger state-owned-enterprise (SOE) shares.

To gain more insights into how the pollution distribution changes upon export liberalization, we utilize firm-level pollution emissions across regions. First, for each industry we divide all prefectures into two regions according to prefecture-level *ex-ante* pollution emissions before the WTO accession, a low-pollution region and another high-pollution region. Then we construct the aggregate water pollution emission in the high-pollution region relative to that in the low-pollution region for every year and each industry. Using the same DID estimation strategy we show that the relative water pollution emission in the high-pollution region decreases after export liberalization, suggesting relatively more water pollution emission in the *ex-ante* low-pollution regions. This is consistent with the deglomeration effect of export liberalization on pollution emissions within the liberalized industry. We further decompose the relative water pollution into the intensive margin and extensive margin. The intensive margin is the relative of average pollution emissions between two regions and the extensive margin is the relative number of polluting firms between two regions. It is then found that the intensive margin is playing a significant role whereas the extensive margin is not statistically significant. In other words, firms in the high-pollution region emit less pollution on average relative to firms in the low-pollution region after export liberalization.[8] Our findings hence highlight the environmental distributional impact of trade liberalization.

Our paper relates to several strands of researches. First, it belongs to the branch of literature discussing the effect of trade on local environment and pollution.[9] Early studies on pollution at the country, regional, or industry level include Grossman and Krueger (1995), Copeland and Scott Taylor (2003, 2004), Antweiler, Copeland, and Scott Taylor (2001), Frankel and Rose (2005) and Levinson (2009), etc. Recent studies on firm-level pollution include Cherniwchan (2017), Barrows and Ollivier (2020), Gutiérrez and Teshima (2018), Shapiro and Walker (2018) among others. With Chinese data, Bombardini and Li (2020) show that the prefecture-level export expansion in China leads to more local pollution and higher mortality.[10] Rodrigue, Sheng, and Tan (2020) show that exporting reduces air pollution of Chinese manufacturing firms. In addition, Chen, Shao, and Zhao (2021) show that export liberalization actually brings down firm-level water pollution intensity. Instead of pollution level or intensity, this paper focuses on the impact of export liberalization on the geographical concentration of water pollution in China. Our study contributes to the studies on the distributional effect of trade liberalization.

Second, this paper also adds to studies on agglomeration and trade, which emphasizes the importance of trade linkages as causes of observed spatial concentration of economic activities. Head and Mayer (2004) provide for an excellent summary of relevant empirical studies. The spatial concentration of pollution is as important as the concentration of other economic activities studied in this literature due to the negative externality of pollution and the potential increasing return to scale in pollution abatement. The geographical distribution of pollution emission is generally overlooked in existing researches. However, it is of particular importance for the central government's allocation of pollution abatement targets across regional governments. It may also endogenously interact with local enforcement of environmental regulations. Our paper provides important reference by studying the influence of export liberalization on the geographic distribution of pollution emissions.

Third, our empirical identification strategy directly follows the recent literature on trade policy uncertainty. We use the TPU shock to identify the causal impact of export liberalization on firm-level water pollution. Handley and Limão (2015, 2017) have done some pioneering work on the effects of policy uncertainty on trade, investment, and welfare. Pierce and Schott (2016) argue that the decline in US manufacturing employment is related to the reduction in TPU after China's WTO accession. Feng et al. (2017) show that the reduction in TPU leads to China's export expansion. On the domestic side, Ma and Liu (2020) find a positive effect of TPU on indigenous innovation, while Crowley, Meng, and Song (2018) figure out a negative effect of TPU on export participation. Our paper adds to this part of literature by identifying the causal effects of the TPU shock on water pollution agglomeration.

The rest of the paper is organized as follows. Section 2 introduces data sources and variable construction as well as the estimation specifications. Section 3 presents our main empirical findings, various robustness checks, heterogeneous effects along with discussions on the mechanisms. Finally, Section 4 contains some concluding remarks.

2. Empirical strategy

In this section, we first briefly describe the institutional background of trade policy uncertainty (TPU) in China and show the validity of using its exogenous reduction after China's WTO accession to identify the causal impact of export liberalization on the geographic distribution of water pollution emission. Then we introduce the main datasets as well as the construction of our key

[8] Though we do not have direct evidence due to the lack of data on firm-level technology adoption, green innovation or abatement equipment, our finding suggests that there is some "technique effect" that decreases the agglomeration of water pollution across regions. Note that the AESPF have come records of abatement equipment at the firm level, but the valid observations are too few for us to carry out rigorous estimations.

[9] A number of studies investigate the effect of environmental regulations on trade, e.g. Hering and Poncet (2014), Dean, Lovely, and Wang (2009), Cai, Yi, Mingqin, and Linhui (2016), Shi and Zhufeng (2018), Duan, Ji, Lu, and Wang (2019).

[10] Other studies find slightly different results, for instance, Dean (2002) uses pooled provincial data on Chinese water pollution and finds that freer trade aggravates pollution via specialization but mitigates it via income growth, with a beneficial net effect de Sousa, Hering, and Poncet (2015) also find that trade openness reduced pollution across Chinese cities.

variables used in our study. In the end, we present the adopted DID specification for our empirical investigations.

2.1. *Trade policy uncertainty*

Since the United States (US) established NTR with China in 1980, it had granted the MFN tariff treatment to Chinese exporters, which was extended on a provisional basis subject to annual renewal.[11] These annual renewal exercises were politically controversial and uncertain. In the worst case, the export tariff rates for Chinese firms would be raised sharply to the non-MFN rates, also known as the Column 2 tariff rates. This uncertainty about the tariff rates significantly discouraged exporting activities.[12] In October 2000, the US Congress approved granting China permanent normal trade relations (PNTR), which took effect at the end of 2001 upon China's accession to the WTO. At that point of time, the export policy uncertainty between China and the US was eliminated. Previous studies have shown that the removal of TPU created significant export opportunities for Chinese firms, not only to the US market.[13] We follow this line of literature and adopt the differences between the two tariff rates (MFN rates and non-MFN rates, both aggregated from product-level tariff rates for each industry) to measure the pre-WTO TPU level for each industry. The differences between the MFN tariff rates and non-MFN tariff rates are quite large, ranging from 32% to 3.6% across industries, comparing to the average MFN tariff rate at around 3%. Hence the uncertainty is indeed quantitatively significant for Chinese firms' export decisions. When these pre-WTO TPUs were all removed after China's WTO accession, it created a heterogeneous export liberalization shock across industries in China, which offers us a perfect setting to carry out a generalized difference-in-difference estimation to identify the causal effect of export liberalization by comparing across industries.

2.2. *Data and variables*

In this study, we compile our data sample from two sources. The first one is China's *Annual Environmental Survey of Polluting Firms* (AESPF). Since the 1980s, the Ministry of Ecology and Environment has collected rich information on firm-level environment statistics, including emissions of the main pollutants (industrial effluent, smog, COD, NH_3, NO*x*, SO_2, smoke and dust, solid waste, noise, etc.), pollution abatement equipment, and energy consumption (use of freshwater, recycled water, coal, fuel, clean gas, etc.), as well as some basic firm information such as administrative divisions, year of opening, and total output. The survey is the basis of the *Chinese Environmental Yearbook*. The second dataset is the *Annual Survey of Industrial Firms* (ASIF) by the National Bureau of Statistics (NBS) of China. Yearly firm-level characteristics are included, such as type of ownership, value-added output, total export, total assets, employment and wage payment, etc. We use this data to construct relevant time-varying industry-level control variables including the export share, the SOE share among domestic firms, and the number of foreign-invested firms using the Chinese industrial classification (CIC) of each firm. After cleaning the two datasets following the previous literature (Cai & Liu, 2009; Feenstra, Li, & Yu, 2014), we match them with the enterprise names first, and for the remaining unmatched sample we match them with the firm identification numbers again.[14]

To determine the effect of export liberalization on the geographic concentration of water pollution, we restrict our sample period to 1999–2006, covering China's WTO accession at the end of 2001. We have three years of observations before the WTO accession (1999–2001) as well as five years afterward (2002–2006). The Chinese government's tenth five-year plan covers the period 2001–2005. This plan usually sets new goals for economic growth as well as pollution reduction, along with other missions and objectives in the coming five years for all provinces. Our treatment, i.e. TPU removal after the WTO accession, falls within this period. However, our variation of TPU is across industries and we compare the geographical distribution of pollution between different industries before and after 2002 (inclusive). Since the five-year plans vary across provinces and the timing is not strictly coinciding with our TPU shock, we do not think it will severely contaminate our identification strategy. Additionally, we employ alternative sample periods as robustness checks using data from 1998 to 2007 and from 1998 to 2012 as our AESPF data only covers until 2012.[15] Lastly, there was a "two-controls" zone policy implemented in China since 1998, we employ another alternative sample with all firms in the "two-controls" zone as another robustness check.

We now illustrate the two key variables of interest in more detail. Our dependent variable is the geographic agglomeration of water

[11] Pierce and Schott (2016) and Feng et al. (2017) provide more detailed discussions on trade policies between China and the US.

[12] Although this policy uncertainty only affects exports to the US, given the importance of the US market for Chinese exporters, it plays a crucial role in Chinese firms' export decisions. Feng et al. (2017) show evidence that the removal of this TPU significantly encourages firm exporting at the extensive margin. It promotes export not only to the US market but also to other foreign markets. With large fixed costs of exporting, the total expected profit from foreign markets needs to be high enough for firms to export. As a result, uncertain payoff from the US market significantly discourages exporting to all destinations at the extensive margin.

[13] Other types of TPU exist from anti-dumping threats and trade wars between China and its trading partners, even after its WTO accession. Here, TPU only concerns the MFN tariff treatment when exporting to the US. See Crowley et al. (2018) for a study using other type of TPU. Additionally, traditional export liberalization is about the reductions in the applied tariff rates. However, the tariff rates applied to Chinese exporters had been the MFN tariff rates over our sample period. They were already at quite low levels and did not decrease much after China's WTO accession. Hence export liberalization through tariff cuts was not that significant. Nonetheless, we control for this type of export liberalization in our empirical investigations.

[14] We only keep observations with all continuous variables between the 0.5% and 99.5% levels to prevent the possible influences of outliers.

[15] As some variables are not available for year 2008–2012, the controls that we can include for the sample 1998–2012 are limited. Estimations using alternative samples find similar results as our benchmark scenario. Results are available upon request.

pollution emissions across regions in China for each industry. Analogous to the measure of production agglomeration, we adopt the EG index proposed by Ellison and Glaeser (1997) to measure the agglomeration of water pollution emissions based on firm-level pollution data as follows:

$$EG_k = \frac{\sum_{i=1}^{M}(s_{ki} - x_i)^2 - \left(1 - \sum_{i=1}^{M} x_i^2\right)\sum_{j=1}^{N_k} z_j^2}{\left(1 - \sum_{i=1}^{M} x_i^2\right)\left(1 - \sum_{i=1}^{N_k} z_j^2\right)},$$

where s_{ki} is the share of industry k's water pollution emission in area i, M is the number of areas, i.e. number of prefectures or provinces of China, x_i is the share of total water pollution for all industries in area i, and z_j is the share of water pollution for firm j of industry k, N_k is the number of firms of industry k.

Using this method, our dependent variable, EG_{kt}, is constructed for each industry k and year t using firm-level water pollution data over the period of 1999–2006, as follows:

$$EG_{kt} = \frac{G_{kt} - \left(1 - \sum_{i=1}^{M} x_{it}^2\right) H_{kt}}{\left(1 - \sum_{i=1}^{M} x_{it}^2\right)\left(1 - H_{kt}\right)}. \tag{1}$$

where we define the spatial Gini index of water pollution $G_{kt} = \sum_{i=1}^{M}(s_{kit} - x_{it})^2$ and the Herfindahl index $H_{kt} = \sum_{i=1}^{N_{kt}} Z_{jt}^2$. The intuition for the EG index is as follows. The spatial Gini index measures the overall geographical concentration of pollution. It may be positively affected by the agglomeration force, as well as the change in the size distribution of existing pollution emissions across firms. We use this index in our main empirical investigations. Furthermore, to gain more insights, we construct relative pollution emission measures for those *ex-ante* high-pollution regions and test how they change upon export liberalization.

The export liberalization we adopt in this study is taking the form of TPU reduction upon China's WTO accession. The measurement of pre-WTO TPU directly follows the literature. Similar to Pierce and Schott (2016), Feng et al. (2017), and Ma and Liu (2020), we use the gap between MFN and non-MFN tariff rates to measure the export policy uncertainty facing Chinese firms before China's WTO accession. The Harmonization System (HS) 6-digit-level tariff rates are aggregated up to the CIC 4-digit industry level using HS-CIC concordance provided by Brandt, Van Biesebroeck, Wang, and Zhang (2017). Then with industry-level average tariff rates, we measure the TPU for each CIC 4-digit industry as follows:

$$TPU_k = \ ln\ \left(\frac{\tau_k^{non-MFN}}{\tau_k^{MFN}}\right);$$

where TPU_k is the level of TPU for industry k before China's WTO accession, $\tau_k^{non-mfn}$ and τ_k^{mfn} are respectively the average non-MFN tariff rates and MFN tariff rates for each CIC 4-digit industry k in 2001. We also employ TPU measures proposed by Handley and Limão (2015) to check the robustness of our results using a simplified version of their measure as follows:

$$1 - \left(\tau_k^{non-mfn} / \tau_k^{mfn}\right)^{-\sigma}, \text{with } \ \sigma = 2 \ \text{ or } \ 3.$$

Summary statistics for our key variables are displayed in Table 1, including the agglomeration indices for pollution and that for output, the spatial Gini index for pollution distribution, the Herfindahl indices for pollution and output in each industry, along with

Table 1
Summary Statistics.

Variable	Mean	S.D.	5%	95%	N
Pollution EG Index	−0.273	2.637	−2.963	1.534	2775
Output EG Index	0.0380	0.110	−0.0460	0.157	3654
Spatial Gini	0.425	0.562	0	1.344	2775
Number of Firms	4.869	1.446	2.398	7.085	3690
Number of Foreign Firms	2.996	1.484	0	5.236	2774
Average Wage	2.492	0.419	1.852	3.170	3690
Capital Intensity	9.675	1.037	8.429	11.71	3690
Output HHI	0.0860	0.145	0.00500	0.352	3751
Pollution HHI	0.400	0.300	0.0400	1	3070
Share of SOEs	0.261	0.187	0	0.625	2774
TPU	1.437	0.876	0	2.721	2754
SOE Share$_{2001}$	0.647	0.352	0	1	2774
Export Intensity$_{2001}$	0.0370	0.0350	0	0.107	2774
Input Share$_{2001}$	0.508	0.478	0	1	2774
Import Tariff$_{2001}$	0.167	0.103	0.048	0.34	3458
Export Tariff$_{2001}$	0.0540	0.0480	0	0.136	2774

Notes: These are industry-level variables. We take log values for the number of firms; Wage is the log value of wage level in thousands RMB; Capital intensity is defined as the ratio of total assets to total employment; Share of SOEs is the aggregate output share of SOEs in a given industry; SOE Share$_{2001}$ is the SOE output share for a given industry in 2001; Export Intensity$_{2001}$ is the export share of total output for a given industry in 2001; Input Share$_{2001}$ is the share of intermediate inputs in a given industry's output in 2001; Import Tariff$_{2001}$ and Export Tariff$_{2001}$ are the industry-level tariff rates (averaged) in 2001.

other industry-level variables.

To gain a rough picture of the values of TPU and its relationship with pollution agglomeration index, we select ten industries and present their TPU levels, EG index for pollution emission in 2001 and changes in water pollution EG indices from 1999 to 2006 in Table 2. As shown, for some industries the water pollution agglomeration index increases. Though very selective, there seems to be a negative relationship between the TPU levels and the changes in water pollution EG indices. We adopt more rigorous procedures to investigate this relationship below.

2.3. Estimation specification

As discussed above, the pre-WTO TPU levels differ across industries and were all removed upon China's WTO accession at the end of 2001. As a result, the elimination of pre-WTO TPU leads to different magnitudes of export liberalization shock across industries. We adopt a generalized difference-in-difference (DID) approach to estimate the causal effects of export liberalization on the agglomeration of water pollution emissions. The following DID specification is adopted to compare the changes in water pollution agglomeration for industries with high pre-WTO TPU relative to that for industries with low pre-WTO TPU around China's WTO accession:

$$EG_{kt} = \beta \quad TPU_k{}^{*}Post02_t + \boldsymbol{Z}'_{kt}\gamma + \alpha_k + \lambda_t + \varepsilon_{kt},$$

where k and t represent industry and year respectively; EG_{kt} is our variable of interest, i.e. the EG index measuring water pollution agglomeration for industry k at time t; TPU_k is the pre-WTO trade policy uncertainty measure for industry k in 2001 before China's WTO accession; $Post02_t$ is a dummy variable representing the post-WTO period, taking a value of 1 for year 2002 and later, and 0 otherwise; α_k is the industry fixed effects, controlling for all time-invariant industry characteristics; λ_t is the year fixed effects controlling for all yearly common shocks to all industries such as aggregate business cycle fluctuations and national environmental regulations on water pollution; $\boldsymbol{Z}_{kt}$ is a vector of time-varying industry characteristics that may also affect the agglomeration of water pollution. In particular, we include two time-varying industry-level characteristics to control for other ongoing industry-level reforms, including the share of SOEs among domestic firms to control for the ongoing SOE privatization reform and the number of foreign-invested firms to control for FDI deregulation in each industry; and ε_{kt} is the error term. Standard errors are clustered at the CIC 4-digit industry level.

To correctly identify the causal relationship using this DID specification, the TPU shock, i.e. the difference between MFN tariff and non-MFN tariff, must be exogenous and random across industries. Regarding the exogeneity, we follow the literature and argue that the non-MFN tariff rates are exogenous. As Pierce and Schott (2016) highlight that non-MFN tariff rates were set decades ago before China's WTO accession, and remain quite stable over time. On the other hand, the US MFN tariff rates were also set in advance of China's WTO entry in agreement with all WTO member countries, these rates should also be exogenous to Chinese firms. As a result, the pre-WTO TPU level, hence also the TPU reduction shock upon China's WTO accession, should be reasonably exogenous to Chinese firms across different industries. We also check this identifying assumption in our empirical tests.

Regarding the randomness of TPU shock across industries, i.e. the randomness of differences between MFN and non-MFN tariff rates across industries, it may not be guaranteed. Industries subject to very high non-MFN tariff rates are likely selected by some criteria, e.g. selective industry protection policies for various purposes. To address this concern, we carry out some robustness checks to ensure that industries with different pre-WTO TPU levels were comparable before 2002. Additionally, we try to identify the possible industry characteristics that may significantly correlate with the pre-WTO TPU level and then control for their potential effects on the dynamics of our variables of interest upon China's WTO accession. These pre-WTO characteristics include industry-level export intensity, intermediate input share in exports, the share of SOEs, initial export tariff rate, and export tariff changes after WTO entry. We find that export intensity and intermediate input share in exports are significantly correlated with an industry's pre-WTO TPU level. Nevertheless, we include all these potential characteristics as controls in our estimation. Denoting all these industry characteristics by $\boldsymbol{X}_k$, we add $X_k{}^{*}Post02_t$ to our DID specification to control for their potential effects on the agglomeration of water pollution. Our final DID specification for the empirical estimation is then given by:

$$EG_{kt} = \beta \quad TPU_k{}^{*}Post02_t + \boldsymbol{Z}'_{kt}\gamma + Post02_t{}^{*}\boldsymbol{X}_k + \alpha_k + \lambda_t + \varepsilon_{kt}, \tag{2}$$

where $\boldsymbol{X}_k$ are all the possible industry characteristics that may affect the pre-WTO TPU level, $Post02_t{}^{*}\boldsymbol{X}_k$ thus help to control for any potential effects these characteristics may have on our variables of interest in a way similar to the TPU shock.

3. Results

In this section, we first present some graphical results to show the main data patterns for water pollution agglomeration around China's WTO accession at the end of 2001. Then we present the set of results obtained from more rigorous DID estimations.

3.1. Graphical results on water pollution agglomeration

We divide all industries into two groups according to their TPU levels in 2001, a high-TPU group consisting of industries with above-median pre-WTO TPU levels and a low-TPU group consisting of industries with below-median TPU levels. The averages of water pollution EG indices for the two groups are constructed for each year over 1999–2006. And then the average EG index of the high-TPU

Table 2
List of Selected Industries with TPU, EH and Change in EG Index.

Industry	Description	TPU	EG_{01}	Δ EG_{99-06}
4123	Navigation, Meteorology and Ocean Special Instrument Manufacturing	3.44	−0.215	−0.799
3543	Manufacture of Valves and Cocks	2.68	−0.218	−0.906
3142	Technical Glass Products Manufacturing	2.34	−0.416	−0.994
3912	Electric Motor Manufacture	2.68	−0.276	−0.644
2812	Artificial Fibre Manufacturing	1.86	−0.316	−0.128
2421	Ball Manufacturing	1.71	−0.237	−0.0812
4019	Other Communication Equipment Manufacturing	1.52	−0.481	0.005
1391	Manufacture of Starch and Starch products	1.43	−0.150	0.104
1532	Bottled Drinking Water Manufacturing	1.15	−0.510	0.291
2130	Metal Furniture Manufacturing	0	−1.036	0.902

group relative to that of the low-TPU group is plotted in Fig. 1. It is shown that after the WTO accession at the end of 2001 the relative water pollution EG index drops significantly for the high-TPU group. It suggests that export liberalization through TPU reduction reduces the liberalized industries' water pollution agglomeration. Hence the geographical distribution of water pollution becomes less agglomerated after export liberalization.

3.2. *Export liberalization and the agglomeration of pollution*

We present our main empirical findings regarding the effect of export liberalization on water pollution agglomeration in Table 3. Our empirical investigation is based on the specification in Eq. (2) with the time-varying industry-level EG index for water pollution emissions as our dependent variable of interest. We start with the basic DID estimation which includes only industry fixed effects and year fixed effects in column (1). Our regressor of interest, $TPU_k{}^*Post02_t$, is statistically significant at 10% confidence level and negative, suggesting that the geographical concentration of water pollution decreases after 2002 for high-TPU industries. Given that the removal of TPU after WTO accession represents export liberalization in the respective industry, our simple estimation suggests that export liberalization decreases water pollution agglomeration in the liberalized industry.

In column (2), we add several important industry-level time-varying characteristics to control for their potential effects on water pollution concentration. These industry-level variables include the geographic concentration of output, i.e. the EG index for output, the Herfindahl index for output, the total number of firms, average wage level, capital intensity, as well as the number of foreign firms and

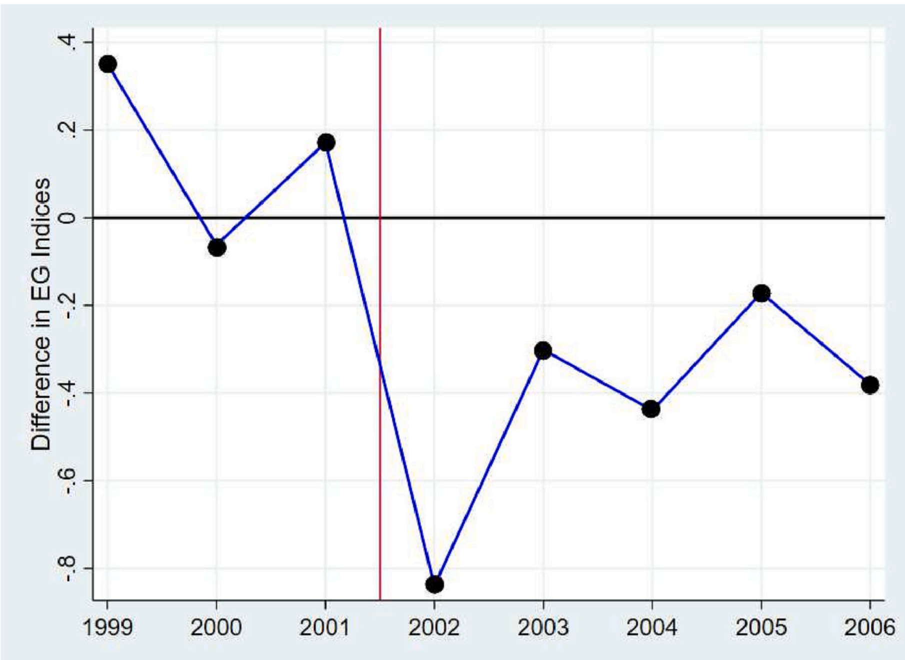

Fig. 1. Relative Water Pollution Agglomeration for High-TPU and Low-TPU Industries.
Notes: Industries are categorized into two groups based on their pre-WTO TPU levels in 2001, a high-TPU group consisting of industries with above-median TPU levels and a low-TPU group consisting of industries with below-median TPU levels. The average water pollution EG indices are calculated for the two groups and the differences between the two group average over 1999–2006 are plotted in this figure.

Table 3
Main Results.

Dependent Variable: EG_{kt}	(1)	(2)	(3)	(4)	(5)
$TPU_k \times Post02_t$	−0.228*	−0.303**	−0.292**	−0.337**	−0.491***
	(0.123)	(0.137)	(0.144)	(0.152)	(0.187)
$TPU_k \times 2001$					−0.177
					(0.332)
$TPU_k \times 2000$					−0.311
					(0.202)
Industry Controls					
Output EG Index		−0.367		−0.397	−0.380
		(1.956)		(2.013)	(2.014)
Output HHI		−1.087		−1.021	−1.087
		(1.947)		(2.017)	(2.025)
Number of Firms		0.469*		0.490*	0.498*
		(0.262)		(0.271)	(0.270)
Average Wage		−0.458		−0.550	−0.552
		(0.501)		(0.526)	(0.526)
Capital Intensity		0.196		0.205	0.202
		(0.252)		(0.255)	(0.255)
Number of Foreign Firms		0.103		0.105	0.103
		(0.114)		(0.123)	(0.123)
Share of SOEs		−0.352		−0.232	−0.232
		(0.532)		(0.550)	(0.551)
$Post02_t \times X_{k2001}$					
$Post02_t \times$ Export $Intensity_{k2001}$			0.961	0.0509	0.0353
			(3.588)	(3.672)	(3.677)
$Post02_t \times$ Input $Share_{k2001}$			0.288	0.313	0.312
			(0.249)	(0.251)	(0.250)
$Post02_t \times$ SOE $Share_{k2001}$			−0.331	−0.387	−0.386
			(0.422)	(0.440)	(0.440)
$Post02_t \times$ Export $Tariff_{k2001}$			−0.398	−0.799	−0.838
			(2.781)	(2.629)	(2.631)
$Post02_t \times$ Import $Tariff_{k2001}$			0.202	0.481	0.469
			(0.910)	(0.899)	(0.905)
FE_{year}	Yes	Yes	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes	Yes	Yes
Observations	2736	2667	2595	2587	2587
R-squared	0.338	0.341	0.336	0.341	0.342

Notes: Standard errors clustered at 4-digit industry level are in the parentheses, and***$p < 0.01$,**$p < 0.05$,*$p < 0.1$.

the share of SOEs among domestic firms to control for other ongoing major reforms in China, i.e. FDI deregulation and SOE privatization reform respectively. Our regressor of interest, $TPU_k{}^* Post02_t$, becomes statistically significant at 5% confidence level and remains negative, confirming the previous result in column (1).

As mentioned in our previous discussion on the DID specification, our export liberalization treatment, i.e. the pre-WTO TPU level, might not be randomly assigned across industries. Hence our treatment and control groups, industries with high and low pre-WTO TPU levels, may be systematically different, as such there may be confounding factors that contaminate our identification. To alleviate this concern, first, as shown in Fig. 1, the water pollution agglomeration for high-TPU and low-TPU industry groups follow very similar paths in the pre-WTO period from 1999 to 2001. This implies that our treatment and control groups are largely comparable before the shock. Second, to further mitigate the concern that non-random pre-WTO TPU levels across industries may bias our estimates, we include interaction terms for industry characteristics that may correlate with pre-WTO TPU and the $Post02_t$ dummy to control for any possible effects of these characteristics on our dependent variable around the WTO accession. As specified in Eq. (2), these potential industry-level characteristics include the industry-level mean export tariff rates in 2001, the export tariff changes after WTO entry, the share of SOEs in 2001, the share of intermediate inputs in exports in 2001, and the industry-level export intensity in 2001.[16] Although we only find that export intensity and input share in exports are the two significantly correlated characteristics, we include all the interaction terms of these characteristics with the $Post02_t$ dummy into our estimation. As shown in column (3) of Table 3, the estimated coefficient for our regressor of interest remains negative and statistically significant.

Then in column (4) we include together all industry-level time-varying control variables as well as the interaction terms as in

[16] For the export tariff changes after WTO entry, we use the MFN tariff changes from 2001 till the end of the sample period 2006.

columns (2) and (3). Similar results are obtained and the magnitude of our estimate of interest does not change much. This alleviates the concern that these time-varying industry control variables may also be affected by the TPU shock and hence may bias our estimates.[17] Results in column (4) are our baseline results using our preferred estimation specification given by Eq. (2). All following robustness checks and heterogeneous effect analysis are also based on this specification.

Firms may have expected China's WTO accession before it actually happened at the end of 2001, and they may have responded to it beforehand. If this expectation effect differs across industries, it might make our treatment and control groups incomparable and hence reject our DID parallel trend assumption. To further ensure that our treatment and control industries are comparable up to the point of TPU shock treatment, and also to test whether there is any anticipation effect before the WTO accession, we include two additional interaction terms, $TPU_k{}^{*}2001$ and $TPU_k{}^{*}2000$ in our estimation. Results in column (5) of Table 3 confirm again that there is no significant difference in pollution EG indices between our treatment and control industries and there is no anticipation effect before 2002. Our main estimate of interest remains statistically significant.

In summary, using a generalized DID estimation strategy, we find that export liberalization by removing the pre-WTO TPU significantly decreases the industry-level water pollution agglomeration in China. Based on our estimation, water pollution agglomeration index drops by about 0.48 for industries with an average level pre-WTO TPU relative to industries with zero pre-WTO TPU after China's WTO accession. This average relative decrease in agglomeration is about 18.4% of the standard deviation for water pollution agglomeration indices in our sample.

3.3. Robustness checks

To ensure the robustness of our benchmark findings, we carry out a series of robustness checks and report the findings in this subsection. All estimations are based on the benchmark in column (4) of Table 3.

3.3.1. Checks on identification assumptions and estimation strategy

We first report the robustness checks for our benchmark results regarding the identification assumptions and other potential concerns regarding the DID estimation strategy. The results of these robustness checks are presented in Table 4.

- *Yearly Dynamic Effect*—It has already been shown that the treatment and control groups are comparable, i.e. following similar trends, before the shock. We conduct an additional test in column (1) of Table 4 to examine the dynamic effects of the TPU shock over time. We replace $TPU_k{}^{*}Post02_t$ with interaction terms between TPU_k and the year dummies from 2000 to 2006, where 1999 is omitted as the base year. We still find that the industry-level pre-WTO TPU has no significant effect on pollution EG index in 2000 and 2001, meaning that the water pollution agglomeration for industries with different pre-WTO TPU levels are balanced before the WTO accession. After the WTO accession, the elimination of TPU has a negative, statistically significant and persistent effect on the industry-level water pollution agglomeration every year. Therefore, the decline in the agglomeration of water pollution in the liberalized industry due to export liberalization is not reversed afterward.
- *Pre-WTO Period*—Similar to the previous investigations, another placebo test we carry out is using the pre-WTO period sample as in Topalova (2010). We check if there is any effect of yearly industry-level TPU on the agglomeration of water pollution using only the pre-WTO sample period. For our DID strategy to work properly, the TPU level should not be systemically correlated with our variable of interest in the pre-WTO period. Hence, we do not expect any significant effect of TPU on water pollution agglomeration in this period; otherwise, it could indicate the existence of some underlying confounding factors. As displayed in column (2) of Table 4, the insignificant coefficient on TPU_{kt} indicates that the TPU has no effect on water pollution agglomeration during the pre-WTO sample period.
- *Industry Time Trend*—The geographical concentration of water pollution may have followed different time trends across industries due to exogenous technological advancements or environmental regulations. If this trend of technological progress or regulations are somehow correlated with the pre-WTO TPU levels across industries, it might contaminate our DID estimates. In particular, these different trends may be picked up by our regressor of interest. In order to mitigate this concern, we include a linear time trend for each industry in our benchmark DID specification given by Eq. (2). The new results are reported in column (3) of Table 4. Our coefficient for the regressor of interest remains statistically significant and of a magnitude similar to our benchmark case.
- *More Controls*—Even though we controlled the potential effects of industry characteristics on the EG index of water pollution using the interaction terms, $Post02_t{}^{*}X_k$. There may still exist some omitted industry characteristics. In column (4) of Table 4, we further include the interaction terms of initial industry pollution intensity, i.e. COD intensity in 2001, capital intensity and average wage in 2001, multiplied by $Post02_t$. The estimation results find no significant effects for these interaction terms. Our main regressor of interest remains statistically significant.

3.3.2. Additional robustness checks

Additional robustness checks regarding the construction of our key variables and estimation standard errors are carried out in this subsection and the results are presented in Table 5.

[17] We further check using the output EG index and output HHI as our variable of interest and find no significant effect of TPU shock on these variables.

Table 4
Robustness Checks on the Identifying Assumptions.

Dependent variable:	(1)	(2)	(3)	(4)
EG_{kt}	Yearly	Pre-WTO	Time Trend	More Controls
$TPU_k \times Post_{02}$			−0.352**	−.340**
			(0.175)	(0.156)
$TPU_k \times 2000$	−0.311			
	(0.201)			
$TPU_k \times 2001$	−0.178			
	(0.332)			
$TPU_k \times 2002$	−0.608**			
	(0.289)			
$TPU_k \times 2003$	−0.590**			
	(0.290)			
$TPU_k \times 2004$	−0.546***			
	(0.197)			
$TPU_k \times 2005$	−0.328*			
	(0.188)			
$TPU_k \times 2006$	−0.447**			
	(0.199)			
TPU_{kt}		−0.182		
		(0.181)		
$Post02_t \times \text{COD Intensity}_{k2001}$				0.310
				(0.309)
$Post02_t \times \text{Capital Intensity}_{k2001}$				−0.034
				(0.103)
$Post02_t \times \text{Average Wage}_{k2001}$				0.180
				(0.390)
Controls	Yes	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes	Yes
$FE_{Industry}$	Yes	Yes	Yes	Yes
Observations	2587	896	2587	2587
R-squared	0.341	0.342	0.480	0.341

Notes: Standard errors clustered at 4-digit-industry-year level are in parentheses, and $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include all Industry Controls and $Post02_t \times X_{k2001}$ as in column (3) of the main results table. Column (1) presents the yearly effects of TPU shock. Column (2) is a placebo test using the pre-shock sample. In column (3), we include industry linear time trend into our baseline estimation. In column (4), we further control the potential effects of some other industry characteristics on our dependent variable, including the initial water pollution intensity measured by COD ratio of total output, initial capital intensity and average wage level.

Table 5
Other Robustness Checks.

Dependent Variable:	(1)	(2)	(3)	(4)
EG_{kt}	$\sigma = 2$	$\sigma = 3$	Two-Stage	Province-Level
$TPU_k \times Post02_t$	−0.714*	−0.691*	−0.359**	−0.340**
	(0.384)	(0.382))	(0.173)	(0.0163)
Controls	Yes	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes	Yes
Observations	2572	2572	690	2576
R-squared	0.340	0.340	0.624	0.326

Notes: Standard errors clustered at 4-digit-industry-year level are in parentheses, and $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Controls include all Industry Controls and $Post02_t \times X_{k2001}$ as in column (3) of the main results table. Column (1) and (2) are robustness checks using two alternative TPU measures. In column (3), we estimate a two-stage DID regression. In column (4), we construct all agglomeration indices at the province level instead of prefecture level.

- *Alternative TPU Measure*—As discussed in the data and variable construction above, we employ two alternative TPU measures proposed by Handley and Limão (2015) to check the robustness of our results. Two simplified versions of their measure are used in columns (1) and (2) of Table 5 respectively. It is shown that the estimates of our regressor of interest remain negative and statistically significant at the 10% significance level, implying that our findings are not driven by a particular method of TPU definitions.
- *Two-Period Estimation*—Another common concern regarding the DID estimation is the construction of standard errors and statistical inferences of the estimated coefficients. We have followed the standard practice to cluster standard errors at the CIC 4-digit industry level, the same as the level of our export liberalization treatment. For robustness, we use an alternative approach suggested by Bertrand, Duflo, and Mullainathan (2004) and collapse the panel structure into two periods, one before and one after the WTO

accession, and then use the White-robust standard errors. Results in column (3) of Table 5 confirm that our main findings are robust and remain statistically significant.

- *Province-Level EG Index*—When constructing the EG index for water pollution agglomeration, we need to specify the space unit. In the benchmark case, we use the prefecture level and construct the EG index for water pollution agglomeration across different prefectures in China. Alternatively, we can construct the EG index for water pollution agglomeration across different provinces in China. Column (4) of Table 5 updates our estimates using this alternative measure of water pollution agglomeration. Again we find very similar results as the benchmark case. It suggests that our export liberalization decreases the geographical concentration of water pollution both at the prefecture level and at the province level.

- *Alternative Samples*—The version of ASIF data that we have is from 1999 to 2006, which is the base for our empirical investigation. Other versions of the data covering different time periods are also adopted by other researchers. To ensure the robustness of our sample choice, as well as to alleviate the concern that we have too short periods before and/or after the shock, we also adopt other samples to repeat our baseline estimations. The results using data from 1998 to 2007, and that from 1998 to 2012 are presented in columns (1) and (2) respectively in Table 6. China has a "two-controls" zone policy on pollution control implemented since 1998.[18] One may worry that this policy may affect the geographical distribution of pollution upon export liberalization. Though this policy is location-based and is not likely to affect our cross-industry identification, we restrict our sample to firms within the "two-controls" zone. Similar results are found and presented in column (3) of Table 6, suggesting that the effect of export liberalization on the geographical distribution of pollution is not significantly affected by this policy.

3.4. Heterogeneous effects

So far we have established the negative causal effect of export liberalization on the geographical agglomeration of water pollution. This is the average effect across all industries. In this subsection, we check whether this effect differs across across industries with heterogeneous capital intensity, water pollution intensity, average wage rate, and firm ownership share.

Firstly, we divide all industries into two groups by their pre-shock capital intensities. Then two benchmark estimations are carried out using each group as the sample. The results in columns (1) and (2) of Table 7 show that the negative causal effect is not significant in the high-capital-intensity industry group, but significant at the 10% level in the low-capital-intensity group. Secondly, we divide all industries into two groups by their water pollution intensities, which is averaged from firm-level water pollution intensities within each industry. The results in columns (3) and (4) of Table 7 show that the negative causal effect is only statistically significant in those industries with higher pollution intensities. Thirdly, we separate industries by their average wage levels into two industry groups. The estimation results presented in columns (5) and (6) of Table 7 suggest that the negative effect of export liberalization on pollution agglomeration is only statistically significant in the low-wage industry group. Given the negative correlation between capital intensity and pollution intensity, between average wage rate and pollution intensity, these heterogeneous results imply that the negative effect of export liberalization on pollution agglomeration is more significant in dirty industries with lower capital intensities and lower wage rates.[19]

One may think that the pollution emissions for firms of different ownership types may respond to export liberalization differently. Hence the composition of ownership types for each industry may matter. In Table 8, we investigate the heterogeneity across industries in firm ownership shares, including the presence of FDIs and the share of SOEs for each industry. We first divide all industries into two groups by the number of foreign firms in each industry. The estimation results for the two groups of industries are presented in columns (1) and (2) of Table 8. It is shown that the negative effect of export liberalization on water pollution agglomeration is statistically significant only in industries with higher presence of foreign firms. Analogously, we divide all industries by their SOE shares into two groups and then run the estimation of Eq. (2) separately for the two groups. Estimated results presented in columns (3) and (4) of Table 8 suggest that the negative causal effect of export liberalization on pollution agglomeration is only statistically significant among those industries with higher SOE shares. These heterogeneity results indicate that the FDI presence and SOE presence are both important for our finding.

3.5. Discussion

3.5.1. Pollution distribution across regions

Now we turn to the discussion on the possible mechanisms that may drive the negative causal effect of export liberalization on the agglomeration of water pollution as well as its policy implications. The decrease of EG index means a deglomeration of water pollution emissions in the liberalized industry, suggesting more pollution emissions in *ex-ante* less-polluted areas. To directly check if this is true, we first divide all prefectures into two regions. For each industry, all prefectures are grouped into two regions according to the prefecture-level water pollution emissions in 2001, a low-pollution region with prefecture-level water pollution emissions below the median level and a high-pollution region with above-median prefecture-level water pollution emission. This grouping does not change over time. The two regions are referred to as the *ex-ante* high-pollution and low-pollution regions.

[18] See Cai et al. (2016) for more discussion on this policy.

[19] Note that even though the estimates for high-capital-intensity, high-wage-rate, low-pollution intensity industries are not statistically significant, they are all negative.

Table 6
Alternative Samples.

Dependent variable:	(1)	(2)	(3)
EG_{kt}	1998–2007	1998–2012	Two-Controls Zone Sample
$TPU_k \times Post_{02}$	−0.247**	−0.164*	−0.0180**
	(0.122)	(0.0987)	(0.00866)
Controls	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes
Observations	3,095	4,633	2,429
R-squared	0.310	0.264	0.350

Note: Standard errors are clustered at 4-digit-industry level, are in parentheses, and ***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. Controls include all Industry Controls and X × $Post_{02}$.

Table 7
Heterogeneous Effects: Capital Intensity, Wage and Pollution Intensity.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
EG_{kt}	Captain Intensity		Pollution Intensity		Average Wage	
	Higher	Lower	Higher	Lower	Higher	Lower
$TPU_k \times Post02_t$	−0.248	−0.482*	−0.415*	−0.244	−0.0782	−0.575**
	(0.179)	(0.266)	(0.235)	(0.193)	(0.209)	(0.229)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1309	1170	1294	1185	1246	1193
R-squared	0.326	0.352	0.305	0.397	0.341	0.335

Notes: Standard errors clustered at 4-digit-industry-year level are in parentheses, and ***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. Controls include all Industry Controls and $Post02_t \times X_{k2001}$ as in column (3) of the main results table.

Table 8
Heterogeneous Effects: Ownership Structure.

Dependent variable:	(1)	(2)	(3)	(4)
EG_{kt}	Number of Foreign Firms		SOE Share	
	Higher	Lower	Higher	Lower
$TPU_k \times Post02_t$	−0.350**	−0.292	−0.551**	−0.190
	(0.161)	(0.250)	(0.218)	(0.212)
Controls	Yes	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes	Yes
Observations	1162	1425	1115	1472
R-squared	0.311	0.355	0.328	0.359

Notes: Standard errors clustered at 4-digit-industry-year level are in parentheses, and ***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. Controls include all Industry Controls and $Post02_t \times X_{k2001}$ as in column (3) of the main results table.

Then for each industry and year, we construct the aggregate water pollution emissions, the firm-level average water pollution emissions, the total number of polluting firms for the two regions. Based on these data, for each industry and year, we construct three variables of interest: the relative water pollution emission in the high-pollution region, the relative average water pollution emission (the intensive margin), and the relative number of water pollution emitting firms (the extensive margin).

Using the same generalized DID specification as Eq. (2), we check how industry-level export liberalization affects the above three variables of interest. The estimation results are presented in Table 9.

As shown in column (1), export liberalization (high pre-WTO TPU level) decreases the relative aggregate water pollution emissions in the *ex-ante* high-pollution region, consistent with the deglomeration effect we find in the baseline estimation. After export liberalization, there are indeed more water pollution emissions in the *ex-ante* low-pollution region.

We then decompose the relative pollution emission into the intensive and the extensive margins, i.e. the relative average water pollution emission and the relative number of polluting firms. The estimation results are shown in columns (2) and (3) respectively, and we find that it is mainly the intensive margin at work. The relative average pollution emission in the *ex-ante* high-pollution region is decreased after export liberalization. This pattern may arise from a stronger "technique effect" or stricter regulation enforcement in the *ex-ante* high-pollution region. Given the insignificant effect on the extensive margin, we tend to believe it is the "technique effect" that decreases the pollution emission at the intensive margin in high-pollution region. Nonetheless, due to the lack of data on

Table 9
Mechanism.

	(1)	(2)	(3)
Dependent variable:	Relative Pollution	Intensive Margin	Extensive Margin
$TPU_k \times Post_{02}$	−0.446**	−0.203**	−0.183
	(0.183)	(0.0846)	(0.126)
Controls	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes
$FE_{industry}$	Yes	Yes	Yes
Observations	2,001	1,930	1,930
R-squared	0.430	0.349	0.533

Note: Prefectures are divided into two regions according to their *ex-ante* water pollution emissions in 2001 for each industry. Then for the high-pollution region and low-pollution region, the relative pollution is constructed for each industry and year. It is further decomposed into a intensive margin and an extensive margin. Standard errors are clustered at 4-digit-industry level, are in parentheses, and $***p < 0.01, **p < 0.05, *p < 0.1$. Controls include Industry Controls and $X \times Post_{02}$.

technology adoption, green innovation or abatement equipment, we are not able to provide direct evidence for this "technique effect". We see this as an important future research project once relevant data is available.[20]

Corresponding to our investigations on heterogeneous effects above, we carry out the same investigations as in Table 9 for different industry groups.[21] Very similar results are found for industries with more FDI presence, higher SOE share, lower capital intensity and lower wage levels. In all these cases with significant negative causal effects of export liberalization on water pollution agglomeration, the results are reconfirmed by the changes in relative pollution for the *ex-ante* high-pollution region. And in all these cases, it is also the intensive margin (relative firm-average pollution emission) that is significant and driving the deglomeration of water pollution emissions instead of the extensive margin (relative number of polluting firms). Our heterogeneous effect analysis seems to suggest that the "technique effect" is stronger in those industries with more FDIs and those with more SOEs.

3.5.2. *Export liberalization and pollution across cities*

To understand more about the effect of export liberalization on water pollution across regions, we carry out another difference-in-difference investigation at the city level. Similar as Bombardini and Li (2020), we construct a Bartik style instrument for each city's export liberalization. We aggregate the industry-level TPU as measured in section 2.2 for each city using its pre-existing industry shares as weights. Then we carry out the DID investigation by comparing city-level water pollution before and after the WTO accession. The set of results are presented in Table 10.

In column (1), the results show that export liberalization decreases the total water pollution emissions in liberalized cities relative to other cities, though with marginal significance. This result is somewhat different from Bombardini and Li (2020) where they find that export liberalization increases air pollution in more liberalized cities. These different findings suggest that different pollutants may respond differently to trade liberalization, as also highlighted by Cole and Elliot (2003). Given that *ex-ante* there are relatively more water pollution in coastal cities which are also more liberalized after the WTO accession, this result may suggest that relatively more water pollution is emitted in those *ex-ante* cleaner cities. It is in line with our main finding that industry-level export liberalization generates a deglomeration effect and more water pollution is emitted in those previously cleaner areas. Hence this city-level analysis reconfirms our industry-level analysis.

In columns (2) and (3), we further decompose the city-level total water pollution into two margins, the intensive margin measuring average water pollution per firm and the extensive margin measuring the number of polluting firms. The DID investigations reveal that it is again mainly the intensive margin (pollution per firm) rather than the extensive margin (number of polluting firms) that is driving the city-level results. It also suggests that there may be a "technique effect" or stricter environmental regulation enforcement in more liberalized cities.

Our cross-city comparison highlights the distributional impacts of export liberalization on water pollution across cities, resonating with the uneven distributional impact of export liberalization on output growth.

4. Conclusion

This paper investigates the potential effect of export liberalization on the geographic distribution of water pollution emissions in China. With data on water pollution around China's WTO accession, we identify a negative causal effect of export liberalization on the agglomeration of water pollution using trade policy uncertainty reduction as the export liberalization shock. Our findings suggest that export liberalization causes deglomeration of water pollution emissions in the liberalized industry, meaning that relatively more water pollution are emitted in those previously low-pollution regions after the export liberalization. This pattern is reconfirmed using relative water pollution between *ex-ante* high-pollution and low-pollution regions for each industry. Further decomposition shows that

[20] Though the AESPF has some records of firm-level pollution abatement equipment, the valid observations are too few after we match with the ASIF data set. No meaningful results are found using the limited sample.
[21] Estimation results are available from the authors upon request.

Table 10
City-Level TPU Shock on Water Pollution.

Dependent variable:	(1)	(2)	(3)
COD_{ct}	Total	Intensive Margin	Extensive Margin
$TPU_c \times Post02_t$	−0.392*	−0.413**	0.0203
	(0.206)	(0.192)	(0.0638)
Controls	Yes	Yes	Yes
FE_{year}	Yes	Yes	Yes
FE_{city}	Yes	Yes	Yes
Observations	2107	2107	2107
R-squared	0.642	0.525	0.910

Note: Controls include time-varying city-level population, GDP, second-industry output share, fixed asset. Standard errors clustered at the city-year level are in parentheses, and***$p < 0.01$,**$p < 0.05$,*$p < 0.1$.

it is the intensive margin (average pollution emission) rather than the extensive margin (number of polluting firms) that drives the deglomeration of water pollution emissions within the liberalized industry. Additionally, this deglomeration effect of export liberalization on water pollution emission is stronger for industries with lower capital intensity and lower average wage levels. And this effect mainly applies to industries with high water pollution intensities. Lastly, city-level analysis seems to suggest that export liberalization decreases relative water pollution emissions.

Our finding has important implications for regional environmental regulations. As water pollution gets less geographically concentrated after export liberalization, relatively more pollution abatement resources need to be allocated to those previously less-polluted regions. Given that *ex-ante* low-pollution regions usually have weaker environmental regulations and weaker enforcement, our finding also calls for active engagement of regional governments particularly in those *ex-ante* low-pollution regions.

Data availability

The data that has been used is confidential.

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