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ABSTRACT

Importing Air Pollution? Evidence from China's Plastic Waste Imports*

Plastic waste trade has grown considerably in the last decades and has caused severe environmental problems in recipient countries. As the largest recipient, China has permanently banned the imports of plastic waste since 2018. This paper examines the causal effect of plastic waste imports on air pollution by exploiting China's experience of importing plastic waste and the recent import ban. Combining data on plastic waste imports with PM2.5 data at the city level for the years 2000-2011, we find that plastic waste imports increased PM2.5 density significantly. This effect is linked to expanded production in the waste processing sector and an increased number of incineration. To evaluate the impact of the import ban on air quality, we employ daily data on air pollution between 2015 and 2020. Our difference-in-differences results show that affected cities, relative to other cities, experienced a significant improvement in air quality following the ban. These findings suggest potential environmental gains from banning plastic waste imports in other countries.

JEL Classification: plastic waste trade, waste import ban, air pollution, $PM_{2.5}$, China

Keywords: F18, F64, Q53, Q56

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1 Introduction

Global trade in waste and scrap has rocketed since the early 1990s, reaching more than two million tons in 2011, an increase of more than five times in the last two decades (Kellenberg, 2015; Gregson and Crang, 2015; Li et al., 2021). Plastic waste trade has contributed considerably to this growth, with a growth rate of 546% from 1996 to 2018.[1] The consequent environmental problems have been at the forefront of public debates (e.g. UNEP, 2019; Roger, 2022; UNEP, 2022). Yet, quantitative analysis is still scarce. Although investigating the environmental effects of trade is a pertinent research area in the international trade literature, and ample empirical evidence is available to date in various contexts (see Copeland et al., 2021, for a review), the role of waste trade has been yet largely neglected (Zhao et al., 2021). This paper fills this gap by estimating the causal impact of plastic waste imports on air pollution in the context of China.

While plastic has become a major commodity globally, the management of plastic waste has been very challenging. Plastic materials have a long natural degrading process, leading to a high environmental cost of waste disposal. Plastic waste recycling has not yet been cost-effective in many countries, especially in those with high environmental standards. According to Geyer et al. (2017), only 9% of plastic waste is recycled, with the remaining either being incinerated or dumped in landfills, causing serious environmental problems and adverse impacts on human health and development (see Manzoor et al., 2020, for a review). Exporting plastic waste to other countries has provided a simple outlet for many – in particular industrialised – countries to deal with their overwhelming plastic waste and circumvent domestic environmental problems (Brooks et al., 2018). The vast majority of plastic waste is shipped from Global North to Global South (Gregson and Crang, 2015; Brooks et al., 2018). This has deteriorated the environment in developing countries due to their less developed waste processing technologies and management practices (Ray, 2008). In this paper, we are interested in the plastic waste trade induced environmental effects in developing countries and specifically focus on air pollution.

China provides an ideal context to study this question for various reasons. First, following its accession to the WTO in 2001, China experienced a boom in plastic waste imports, rendering it the world's largest recipient in the early 2010s. As of 2016, China received 45.1% of global accumulated plastic waste exports (Brooks et al., 2018).[2] Second, during the same period, China experienced rapid deterioration in environmental quality. While this could be due to

[1] Own calculation with data retrieved from the World Integrated Trade Solution (WITS) database.

[2] Hong Kong imported 27.3%, ranked the second on the importing list. As Hong Kong is the entry port of mainland China with a large majority of its imports being further shipped to China, more than half of global plastic waste exports are designated in China (Brooks et al., 2018).

various reasons, such as heavy reliance on fuel consumption and lax environmental regulations (Greenstone et al., 2021), increased imports of plastic waste is also potentially a vital driving force given the drastic growth.[3] Further, realizing the worsening environmental problems, China declared a “war on pollution” in 2014 and has implemented a series of regulations that aim to improve environmental quality, including a ban on plastic waste imports that has been effectively enforced since January 2018. Afterwards, imports of plastic waste have reduced significantly to a minimal level. The import ban provides us with a natural experimental setting to empirically examine whether air quality improves in heavily affected cities following the ban relative to less affected cities.

China’s imports of plastic waste and the environmental quality experienced a clear transition around 2014. Before that, both plastic waste imports and air pollution show a rising trend, whereas both have witnessed significant declines afterwards. Thus, our empirical analysis is divided into two parts. First, we analyse the effect of rising plastic waste imports on air pollution in recipient cities and in the second part we evaluate the effectiveness of the plastic waste import ban in improving air quality.

To analyze the impact of plastic waste imports on air pollution, we rely on the transaction-level customs data between 2000 and 2011 that record the universe of all imports at the Harmonized System (HS) 8-digit product level, allowing us to identify plastic waste products. Additionally, they record the final destination of shipments at the prefecture city level, enabling us to link the processing of imported plastic waste in the destination city to local air pollution. Specifically, we aggregate imports of all plastic waste types to the destination city level and regress the average concentration of particulate matter (PM) 2.5, our main measure of air pollution, on city-level plastic waste imports.

Estimating the causal effects of plastic waste imports on air pollution is challenging because imports of plastic waste could be driven by local demand. Cities with a large waste processing sector may be more likely to import plastic waste. At the same time, pollution in those cities may be more severe due to the large scale of waste processing, which involves by nature pollution-intensive activities. On the contrary, air quality may be better in those cities if they develop more environmental friendly technology. These two alternative cases would create upward or downward biases in our estimates.

To solve the endogeneity problem, we first include a set of city-level controls in our estimations, such as GDP per capita, sectoral composition, the size of local plastic production, and the share

[3] Substantial geographical and temporal variations in both plastic waste imports and air pollution allow us to uncover possible relations between the two.

of pollution-intensive sectors, to capture local demand attributed to those factors. The inclusion of GDP per capita additionally controls for the income channel through which imported plastic waste could benefit the local environment by contributing to the growth of the waste processing industry and/or the plastics industry, thereby allowing us to concentrate on the direct effects on air pollution.

Second, we utilise an instrumental variable approach using two alternative instrumental variables. Following the trade literature (Hummels et al., 2014; Mayer et al., 2021), we explore the exogenous variation in global plastic waste export supply by aggregating total plastic waste exports of all countries, minus exports to China. To create a city-level measure of the instrumental variable, we multiply the aggregate plastic waste export supply with the average tendency of importing for each city. The average tendency is calculated as the fraction of years for which a city imported plastic waste between 2000 and 2011 following the aid literature (see e.g. Nunn and Qian, 2014; Dreher et al., 2021). Causal inference using this instrumental variable relies on the assumption that cities with a higher average probability of importing plastic waste are more affected by growth in the global total export supply of plastic waste, conditional on city and year fixed effects as well as a series of control variables. Our second instrumental variable exploits the fact that bulk plastic waste imports enter China mainly through port cities. Given the high transportation costs of plastic waste, cities with a larger distance from the port are less likely to import. The second instrumental variable is thereby constructed as the interaction between plastic waste export supply and the inverse of the distance to the nearest port. As additional robustness checks, we replace the global total export supply with the total value of plastic waste imports by Southeast Asian (SEA) countries, which is then interacted with the average importing probability of Chinese cities or the inverse of the distance to the nearest port. This derives from SEA countries being among the major destinations of plastic waste shipments following China. With an increase in global export supply, both China and SEA countries would experience higher imports.

To evaluate the impact of the 2018 import ban on air quality, we explore the uneven distribution of cities that are affected by the ban. Utilising daily data from 2015 to 2020 on various measures of air pollutants, we are able to identify the causal effect of the ban on air quality by comparing the air quality of affected cities before and after the ban relative to unaffected cities in a difference-in-differences (DiD) framework. Due to a lack of data on plastic waste imports at the city level right before the ban, we rely on cities' historical records of plastic waste imports in the years 2000-2011 and define affected cities as those importing plastic waste products in any years during that time. This approach leans on the assumption of serial correlations of imports over time, such that cities that imported plastic waste in earlier years are more likely to import in later years and are more likely to be affected by the ban. In several robustness checks, we identify treatment cities using alternative criteria, including importing plastic waste for at least four years, the median length of importing, or at least six years, corresponding to a probability of 50 percent, as well as using the probability of importing directly.

Our empirical results show that plastic waste imports significantly increased PM2.5 density in Chinese cities from 2000 to 2011. These effects are confirmed by the 2SLS estimations using alternative instrumental variables. Our preferred estimation implies that an average increase in plastic waste imports during the sample period (i.e. 50.2 percent) raises $PM_{2.5}$ concentration by 2.5 percent, evaluating at the mean and holding all other things constant. We show that our estimates are not driven by pre-trends or imports of other types of waste, and are robust to alternative measures of $PM_{2.5}$ density, additional controls of economic and trade factors as well as the possible impact of the Two Control Zones (TCZ) policy, which is the major environmental regulations imposed during our sample period.

Our results based on the second sample period indicate a significant improvement in air quality in affected cities after the import ban relative to unaffected cities. On average, the ban reduces $PM_{2.5}$ density by 3.7 $\mu g/m^3$, corresponding to 8.5 percent of the sample average. Using other measures of air quality, we find that the plastic waste import ban reduces emissions of SO_2, NO_2, PM_{10}, as well as the air quality index (AQI), reassuring the air quality improving effects.

To understand how plastic waste imports affect air pollution, we specifically examine two channels, the "production channel" and the "incineration channel". The first channel indicates increased air pollution due to expanded processing of plastic waste, whereas the latter indicates air pollution generated during the incineration of disposed plastic waste. We find that cities that import more plastic waste tend to have a larger scale of plastic waste processing and a larger number of newly registered plastic waste processing firms, especially private firms. We also find that imports of plastic waste induce an increased number of open-air fires.

This paper is closely related to the large body of literature that studies the environmental effects of international trade. This literature traces back to Grossman and Krueger (1991) who discuss the environmental impact of NAFTA. With improved data availability, several empirical studies have shown evidence on the relationship between trade and the environment. The findings, however, are far from conclusive (e.g. de Sousa et al., 2015; Cherniwchan, 2017; Shapiro and Walker, 2018; Gutiérrez and Teshima, 2018; Bombardini and Li, 2020; Cui et al., 2020; Wang, 2021). One reason is that the majority of existing studies consider measures of trade in all products, which could affect the environment through a variety of channels that work in opposite directions (Copeland et al., 2021). In this paper, we focus on trade in waste, which has been much less studied. Compared to the trade of other products, the impact of waste trade on the environment is relatively straightforward as only a very small share of waste is recycled and the overwhelming majority ends up in landfills or dumpsites, which contaminates the environment (Brooks et al., 2018). To the best of our knowledge, this paper is among the first that examines the causal effects of waste trade on the environment. Our results suggest that although waste takes a relatively small share in total trade, its effect on the environment is not negligible.

This study also contributes to the literature that documents the effects of environmental policies on air quality, especially in China. The air-cleaning actions taken by the Chinese government for the Olympic Games in 2008 and the implementation of fuel standards and driving restrictions in China are found to significantly reduce air pollution (Chen et al., 2013; Viard and Fu, 2015; Li et al., 2020). We complement this stream of literature by investigating a more recent, large-scale environmental policy, the plastic waste import ban, and its effectiveness in improving environmental conditions.

Several studies have discussed the Chinese import ban on plastic waste (e.g. Brooks et al., 2018; Wen et al., 2021) and shown descriptive evidence on its effect on trade flows. One paper that is close to the second part of our analysis is Li and Takeuchi (2021), which investigates the effects of the ban on air quality in Chinese cities. Using daily data on ozone concentrations, they employ a DiD approach and find that the import ban reduces ozone concentration in coastal compared to inland cities. Our paper distinguishes itself from Li and Takeuchi (2021) in several aspects. First, they consider cities in three coastal provinces as the treatment group and cities in three inland provinces as the control group. In contrast, we include all Chinese cities in our analysis and define treatment cities based on their historical records of plastic waste imports. Hence, we can identify the differential effectiveness of the ban across cities more precisely. Second, they use data of 2017 and 2018, whereas in this paper, we use data spanning a longer period (2015 to 2020), which covers the implementation of the second ban effective from December 31, 2018. Third, they consider ozone concentration as the sole measure of air quality. By contrast, our paper uses $PM_{2.5}$ as the primary measure but also considers six additional measures, allowing us to evaluate the impact of the ban on air quality in a more nuanced way. More importantly, besides assessing the effects of the ban, we also examine the effects of plastic waste imports on air pollution using city-level import data for the years 2000-2011. This complements the findings of the import ban and provides a complete picture of the environmental effects of China's experience of waste imports.

The rest of the paper is organised as follows. In Section 2 we provide more information on China's plastic waste imports and its import ban on plastic waste in 2018. Section 3 describes the data and measures of key variables. In Section 4 we perform the first empirical analysis using city-level data between 2000 and 2011 and focus on the effect of the plastic waste imports on air pollution. Section 5 presents the second empirical analysis where we evaluate the impact of the plastic waste import ban on air quality. Finally, Section 6 concludes.

2 Plastic waste imports in China and the import ban

Plastic production skyrocketed in the mid-1990s, provoking a rise in the supply of plastic waste. World total export of plastic waste peaks in 2011 with a trade volume of 7.6 billion USD. Afterwards, it decreases continuously, as shown in Figure 1 that depicts the global trend in plastic waste exports from 1996 to 2020 based on data from the WITS database.

Figure 1: Plastic waste exports by destination over time: 1996-2020

Notes: This figure shows the time trend of world total plastic waste exports, exports to China, exports to non-China markets as well as exports to the south east Asian (SEA) countries (all in billion USD) over the time period of 1996 to 2020. Data are from the WITS database. Plastic waste products are identified according to HS6 codes 391510, 391520, 391530, and 391590. The red dashed line indicates the time of China's plastic waste import ban in 2018.

A substantial share of plastic waste is traded from high-income countries to developing countries (Wen et al., 2021), consistent with the prediction of the "Pollution Haven Hypothesis". It states that high-income countries where environmental protections are stringent tend to locate their pollution-intensive productions in low-income countries with laxer environmental regulations (Copeland and Taylor, 1994).

China has played an important role in the rapid growth of the world export of plastic waste. Since its accession to the WTO in 2001, China has experienced a substantial increase in plastic waste imports and quickly became the world's largest recipient. Until 2018, China received around half of the world's total plastic waste exports (Brooks et al., 2018; Wen et al., 2021). The substantial growth of waste imports in China is partly due to the lax environmental policies relative to its trade partners, which attracts waste inflows from countries with stricter environmental regulations, notably the EU countries and the U.S. (Kellenberg, 2012, 2015; Li et al., 2021). Another reason is the increased domestic demand for cheap intermediate inputs, particularly in the 2000s when China experienced rapid economic growth. Importing plastic waste is one way to meet the demand given the possibility to recycle materials at a very low cost (Li et al., 2021), though the environmental costs are not necessarily low.

Expecting a surge in waste imports following China's WTO accession, the Chinese government published a catalogue of solid wastes in 2002, whose imports were regulated with import licences, and a catalogue of solid wastes that were prohibited from being imported. The two catalogues were updated irregularly over time, and plastic waste was added to the regulated list in 2005. Despite these regulations, the imports of waste, including plastic waste, still experienced substantial growth. In recent years, the Chinese government has become more concerned about environmental pollution and declared a "war on pollution" in 2014, whereby several policies aiming at alleviating environmental pollution have been implemented (Greenstone et al., 2021). Among those policies, the "National Sword Operation" initiative in 2017/18 that permanently banned the imports of four categories of solid waste, including plastic waste, was prominent and has induced remarkable impacts on the global recycling industry.

The Chinese government notified the WTO on July 27, 2017 about implementing a permanent import ban on 24 types of solid waste in four categories: non-industrial waste plastics, unsorted scrap papers, discarded textile materials, and vanadium slags. The ban became officially effective on January 1, 2018. It was the first time that plastic waste appeared on the Chinese import ban list, and the policy has brought about considerable public concerns about plastic waste crises in developed countries (see numerous media reports such as de Freytas-Tamura (2018) and Agence France-Presse (2019)). Additionally, contamination regulations of waste imports were tightened. A new limit of 0.5% contamination in imported waste loads took effect on March 1, 2018.

The ban created a strong effect on the global waste trade market. With limited ability to manage waste domestically in a short time, many countries diverted their waste exports to other countries, mostly to SEA countries, as shown in Figure 1. This caused worries about possible waste crisis in those countries (Jain, 2020). Some of them lately enacted similar bans (The Economist, 2019). Consequently, total world exports of plastic waste decreased sharply (Brooks et al., 2018; Liang et al., 2021, see also Figure 1). To further reduce waste imports, China enforced a second import ban on additional solid waste materials, including the remaining types of plastic waste, namely industrial plastic waste, on December 31, 2018.[4]

In this paper, we focus on plastic waste, although the ban did not solely target plastic waste and the imports of several other types of solid waste were also banned. This is because plastic materials have a crucial role in waste management due to their vast amount and persistence. Inappropriate processing of plastic waste, especially incineration, could generate severe air pollutants, which can be measured well by our data. Additionally, it was the first time in 2018 that plastic waste imports were permanently banned in China. In contrast, the Chinese government started to limit the imports of other types of waste much earlier. From the perspective of identification, focusing on the plastic waste import ban would allow us to evaluate its causal impact on air pollution in a quasi-experimental setting.

Given the divide in the trend of plastic waste imports and environmental policies around 2014, our empirical analysis consists of two parts. The first part investigates the rise in plastic waste imports to China over the period 2000 - 2011, and the second part evaluates the sharp decrease in plastic waste imports in 2018 with the enactment of the import ban on several plastic waste materials.

3 Data and measures

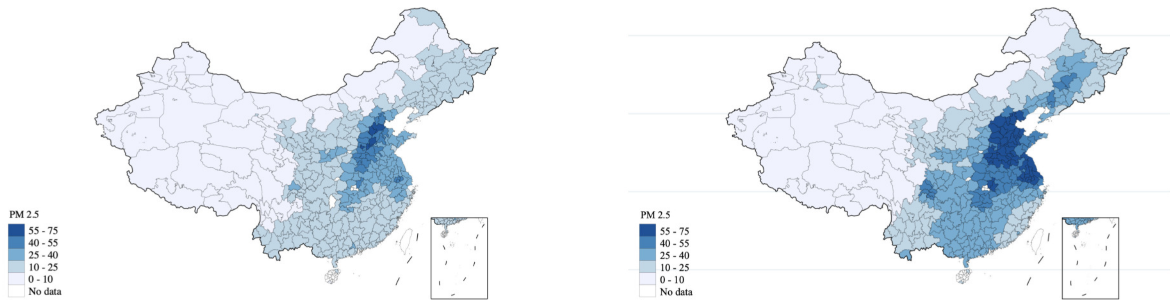
3.1 Measuring air pollution

Our main outcome variable is air pollution measured by $PM_{2.5}$ density.[5] We choose this measure for two reasons. First, $PM_{2.5}$ is one of the major pollutants emitted from plastic waste processing, especially from incineration. Second, data on $PM_{2.5}$ is the only measure available at the city level for the entire sample period spanning 2000 to 2020. In our analysis of later years with better data availability, we also consider other air pollution measures, such as densities of sulphur dioxide, carbon monoxide, etc.

[4] According to the data from the WITS, China imported 39.04 million USD (51.60 thousand tons) of plastic waste in 2018 and only 0.52 million (0.92 thousand tons) in 2019. By contrast, China imported 3263.26 million USD (5828.59 thousand tons) in 2017 and an average of 4645.09 million (7624.00 thousand tons) between 2013 and 2017.

[5] $PM_{2.5}$ indicates small, non-visible particles and liquid droplets in the air composed of different chemicals. Among others, they can be emitted by traffic, fires or industrial production (EPA, 2021). Being inhaled, they can cause severe health problems, mainly respiratory diseases. The World Health Organization considers annual average ambient $PM_{2.5}$ concentrations lower than 5 $\mu g/m^3$ and daily levels less than 15 $\mu g/m^3$ to be safe for health (WHO, 2021).

Our $PM_{2.5}$ measure is from the global annual grid-level data on $PM_{2.5}$ provided by the Socialeconomic Data and Applications Center (SEDAC) of the National Aeronautics and Space Administration (NASA) (Center for International Earth Science Information Network - CIESIN - Columbia University, 2020). This data set reports global $PM_{2.5}$ concentration measures at a 0.01 degree grid cell level for the years 1998 to 2016 by combining multiple satellite-based data sources, and provides a reliable measure of air pollution for earlier years in China when data of air pollution are scarce (Fu et al., 2021). Based on this data set, we calculate the annual average (as well as minimum and maximum) $PM_{2.5}$ density for 334 Chinese prefecture-level cities for the years between 2000 and 2011 when we have data on plastic waste imports. The average annual $PM_{2.5}$ concentration is 31.58 $\mu g/m^3$, ranging from 1.03 to 90.86 $\mu g/m^3$. Figure 2 shows the spatial and temporal heterogeneity in $PM_{2.5}$ concentrations across Chinese cities, mapping $PM_{2.5}$ density per city in 2000 and 2011. In both years, we observe the largest $PM_{2.5}$ density in the east coastal region. The average $PM_{2.5}$ density increases from 2000 to 2011 overall, notably in the east and middle parts of China.



(a) 2000

(b) 2011

Figure 2: $PM_{2.5}$ density by city based on the SEDAC data in 2000 and 2011

Notes: This map shows city-level average $PM_{2.5}$ density in 2000 and 2011. Data on average $PM_{2.5}$ are retrieved from the satellite-based estimates of $PM_{2.5}$ maintained by the Socialeconomic Data and Applications Center (SEDAC) at Columbia University.

As an alternative data source, we utilise the average city-level $PM_{2.5}$ density generated from the Atmospheric Composition Analysis Group (ACAG) (Hammer et al., 2020) to check the robustness of our main results. The ACAG data provide $0.01° \times 0.01°$ pixel-level $PM_{2.5}$ estimates on both yearly and monthly bases from 1998 to 2020 and allow us to generate city-level measures of $PM_{2.5}$ covering the analysis sample period. The average $PM_{2.5}$ density based on this alternative source shows a very similar pattern across cities and years to that of the SEDAC based measure (see Figure A.1 in Appendix A), with an average density of 43.40$\mu g/m^3$.[6]

To analyse of the effect of the plastic import ban in later years, we rely on finer-grained data

[6]The simple correlation between the two measures is 0.77.

provided by China National Environmental Monitoring Centre (CNEMC) which reports daily air quality measures of more than one thousand monitoring stations across China. Besides $PM_{2.5}$, this dataset also reports various further measures of average daily air pollutants, including carbon monoxide (CO), sulphur and nitrogen dioxide (SO_2 and NO_2), ozone (O_3), PM_{10}, as well as the composite air quality index (AQI) calculated based on the six types of air pollutants. The raw data report daily information of 1,488 stations in 334 cities from May 2014. In this paper we use data from January 2015 to December 2020, allowing three years both before and after the implementation of the import ban.

Figure A.2 in Appendix A shows the average $PM_{2.5}$ density over the years $2000 - 2020$ based on the above three data sources. The ACAG measure is larger than the SEDAC measure throughout, but shows a similar time trend. Average $PM_{2.5}$ density increases from 2000 to around 2007, followed by a modest decrease until 2013. Since then, $PM_{2.5}$ density has been decreasing considerably, a pattern confirmed by data from both ACAG and CNEMC. Our analysis samples thereby cover the period when China experienced substantial deterioration of air quality with rapid growth of plastic waste imports and the period when air quality has been improved and plastic waste imports have been permanently banned.

3.2 Measuring city-level plastic waste imports

Our main explanatory variables capture plastic waste imports per city over time. We rely on transaction-level Chinese customs data from 2000 to 2011, maintained by the General Admission of Customs of China (GACC). They cover the universe of Chinese importers and report detailed information for each transaction at the HS 8-digit product level, including importers, total values, source countries, etc. Most importantly, they report the final destination of imports at the city level until 2011. This is crucial for identifying the effect of plastic waste imports on local air quality, as most plastic waste imports entered China through harbour cities and were then shipped to inland regions for processing (see Figure A.3).[7] Measuring plastic waste imports according to their final destination allows us to precisely evaluate which cities were affected. We identify plastic waste products according to the list published by the Ministry of Ecology and Environment of the People's Republic of China that includes five HS-8 digit codes: 39151000 (plastic wastes, parings, and scraps of polymers of ethylene), 39152000 (plastic wastes, parings, and scraps of polymers of styrene), 39153000 (plastic wastes, parings, and scraps of polymers of vinyl chloride), 39159010 (plastic wastes, parings, and scraps of polyethylene terephthalate),

[7] 92.39% of imported plastic waste between 2000 and 2011 arrived at the east and southeast coasts of China, with 40.05% entering China through six ports in Guangdong province and 26.04% through Shanghai.

and 39159090 (other plastic wastes, parings, and scraps).[8] Based on the product-level customs data, we sum up the value of all imported plastic waste products for each city and year.

Figure A.4 in Appendix A maps the value of plastic waste imports for each city for the years 2000 and 2011. It shows that only a small number of cities, notably cities on the southeast coast, imported plastic waste in 2000. In 2011, however, many more cities imported plastic waste, including cities in inland regions.[9] Importantly, the geographical distribution of importing cities covers all broad regions in China and provides enough variation across regions that allows us to identify the environmental effects due to differential intensities of plastic waste imports.

For the later years without data of plastic waste imports at the city level, we construct an indicator variable *Pwaste importer* denoting plastic waste importing cities if they imported any plastic waste during 2000 - 2011. According to this criteria, 275 out of 334 cities are classified as plastic importers. We also consider alternative criteria, such as importing plastic waste for at least four or six years during the sample period or importing plastic waste in 2011, and use the average probability of importing between 2000 and 2011 as a continuous measure of treatment.

3.3 Covariates and mediators

Following the literature (e.g. He et al., 2020; Li et al., 2020; Guo, 2021), we control for a set of weather conditions in our estimations using data from the NCEP daily global reanalysis data set and the CPC Global Precipitation Data provided by the National Oceanic and Atmospheric Administration's (NOAA) Climatic Prediction Center (Kalnay et al., 1996). On a 2.5 degree grid cell level, the NCEP data set reports daily surface temperature in degree Kelvin, relative daily humidity, as well as meridional and zonal wind speed in meters per second. Meridional wind captures wind speed from north to south, and zonal wind measures wind speed along the latitudinal line. Information on precipitation is measured at the 0.5 degree grid cell level and records the total amount of precipitation per day. We aggregate data on these measures to the city level by calculating the average value over the prefectural area.

In the analysis for the years between 2000 and 2011, we additionally control for time variant city-level characteristics. They include local population, GDP per capita, and employment, all in logs, as well as the output shares of the primary and the secondary sectors, which captures the sectoral composition of the local economy. The data are collected from the *China City Statistical Yearbooks* (issues from 2001 to 2012).

[8] See https://www.mee.gov.cn/gkml/hbb/bgg/201708/t20170817_419811.htm.

[9] In 2000, 80 cities out of 334 imported plastic waste products. This number increased to 200 in 2011.

To understand possible channels, we rely on production data from the Annual Survey of Industrial Firms (ASIF) maintained by the National Bureau of Statistics (NBS) of China that collects firm-level data on all state-owned enterprises and above-scale private firms with an annual sales above 5 million Chinese Yuan. Importantly, this database reports the location and the four-digit industry code for each firm, allowing to identify waste processing firms and measure the size of the waste processing sector in each city. We also use the firm registration database that covers the universe of firm registrations in China until 2020. This database makes it possible to examine changes in the number of new plastic waste processing firms as an alternative measure of the change in the waste processing sector. Moreover, we use the information on the exact location and timing of observable fires from the active fire dataset provided by the Earth Observatory Center of NASA (NASA, 2020). This dataset documents occurrences of active fires across the globe. Fires are detected via satellite sensors based on heat signatures. We count the yearly and daily number of active fires per city. Summary statistics of variables used in the analysis of the two periods are reported in Table A.1 and Table A.2 in Appendix A.

4 Plastic waste imports and air pollution: City-level analysis for the years 2000-2011

4.1 Empirical strategy

To estimate the effects of the plastic waste imports on air quality, we regress the average level of $PM_{2.5}$ density on plastic waste imports at the city level conditional on a set of control variables using the empirical specification as follows:

$$PM_{2.5,ct} = \alpha + \beta Pwaste\ imports_{ct} + \gamma \mathbf{X}_{ct} + \theta_c + \phi_t + \epsilon_{ct} \quad (1)$$

where the dependent variable $PM_{2.5,ct}$ denotes the average $PM_{2.5}$ density level of city c in year t. $Pwaste\ imports_{ct}$ indicates the total value of plastic waste imports. To account for the fact that some cities did not import plastic wastes, thereby 0 imports, we transform import values using the inverse hyperbolic sine transformation (*asinh*), which is continuous at 0 and can be interpreted as log point changes with large values (Bellemare and Wichman, 2020). $\mathbf{X}_{ct}$ denotes a set of city-level characteristics that may be correlated with local air quality, including population, employment, GDP per capita, all in logs, as well as the share of non-agriculture population to measure urbanisation and the output shares of the primary and the secondary sectors to capture the effects of local sectoral structures. We also control for a set of weather conditions to absorb possible effects on air quality changes. These include average temperature, wind speed and direction, average humidity, and total rainfalls. θ_c is city fixed effects, capturing the effects of all time-invariant characteristics at the city level. ϕ_t denotes year fixed effects that control for aggregate shocks affecting all cities identically in a particular year, such as macroeconomic changes due to business cycles. ϵ_{ct} is the error term. We cluster standard errors at the city level to allow for possible inter-temporal correlations within cities.

One concern of identifying a causal effect by estimating Equation (1) is the endogeneity of plastic waste imports. As shown in Figure A.4 in Appendix A, cities that imported plastic waste are not randomly distributed. If unobserved determinants of importing plastic waste are correlated with local environmental quality, the estimated effects of plastic waste imports on air quality in Equation (1) would be spurious. One possible factor is the local capacity of processing plastic wastes. Regions with advanced technology in processing plastic waste are more likely to import plastic wastes, especially when there is a surplus capacity to deal with domestic waste. Meanwhile, regions with advanced waste processing technology could recycle waste more efficiently and consequently produce a lower amount of pollutants. As such, failing to control for local technology levels would yield underestimates of the effects of plastic waste imports on air quality.

To deal with the endogeneity of plastic waste imports, we employ an instrumental variable approach by exploring exogenous determinants of cities' importing of plastic wastes. Specifically, we follow the trade literature and construct our instrumental variable by exploiting the world total plastic waste exports supply (Hummels et al., 2014; Mayer et al., 2021). To account for the world export growth of plastic waste due to China's import demand, we exclude exports to China from total world exports. This ensures that world export growth of plastic waste is driven by exogenous changes in export supply. As shown in Figure 1, total world exports of plastic waste, excluding exports to China, show a high correlation with China's imports of plastic waste. Alternatively, we consider plastic waste imports by SEA countries as an alternative instrumental variable since they are among the primary recipients of plastic waste besides China (see Figure 1).[10]

To predict city-level imports of plastic waste following world total plastic waste supply growth,

[10] Autor et al. (2013) and Bernard et al. (2018) use a similar approach and construct the instrumental variable for the imports of American commuting zones and the exports of Norwegian firms by exploring the imports of other developed countries and the exports of other Nordic countries, respectively.

we consider two alternative approaches. The first approach follows the spirit of the aid literature (e.g. Nunn and Qian, 2014; Ahmed, 2016; Dreher and Langlotz, 2020; Dreher et al., 2021) and explores the average probability of importing plastic waste. Specifically, we count the number of years (Num_c) that each city imported plastic waste during our sample period and calculate the propensity of plastic waste imports as $P_c = Num_c/12$. Our instrumental variable is constructed as follows:

$$IV^1_{ct} = Pwaste\ exports^{W \to O}_t \times P_c \tag{2}$$

where $Pwaste\ exports^{W \to O}_t$ denotes the value of world total plastic waste exports minus exports to China. In the robustness check, we replace it with plastic waste imports by SEA countries net of imports from China. In analogue to plastic waste imports, we transform these variables using the inverse hyperbolic sine transformation. This instrumental variable indicates that cities with a higher average probability of importing plastic wastes tend to import more with world export supply growth.

Our second approach exploits the fact that plastic waste imports are often transported through waterways and enter China via ports.[11] Given that waste products are in a high weight but with a low value, transporting them is expensive and is thereby very sensitive to distance (Kellenberg, 2015). It follows that cities further away from China's major ports are less likely to import plastic wastes. The second instrumental variable is consequently constructed as world total export supply divided by each city's distance to the nearest port, as follows:

$$IV^2_{ct} = Pwaste\ exports^{W \to O}_t \times \frac{1}{D_c} \tag{3}$$

One concern with this instrumental variable is that distance to the port could be correlated to other factors that affect the environment, and the exclusion restriction assumption would be violated. For example, east coastal cities in China are in general more developed than inland regions. While economic development could be related to better air quality due to higher income levels and more advanced production technology, intense production activities could also produce more pollutants. The city fixed effects in our baseline regression could partially solve this problem. In addition, we include a set of control variables at the city level to account for local economic growth, industrial structure, labour market conditions, as well as urbanisation, which could further capture other possible channels through which proximity to

[11] Our data show that 67.98% of plastic waste imports to China are transported through waterways.

ports affects environmental quality. As such, this instrumental variable is reasonably exogenous conditional on the rich set of control variables.

4.2 Empirical results

4.2.1 Baseline results

Table 1 reports the estimation results of Equation (1), in which columns $(1) - (3)$ report the OLS estimation results and $(4) - (6)$ report the 2SLS estimation results using world total plastic waste exports times the probability of importing plastic waste of each city as the instrumental variable. In both sets of results, we start from a baseline specification controlling for only city and year fixed effects, as in columns (1) and (4). Then we add city-level control variables in columns (2) and (5) and weather-related control variables in columns (3) and (6).

Both OLS and 2SLS estimations report a positive and highly significant coefficient of plastic waste imports, indicating that cities that import more plastic waste have a higher $PM_{2.5}$ density. The coefficient estimate in our preferred specification with a full set of control variables in column (6) indicates an elasticity of 0.05 evaluated at the average level of plastic waste imports and $PM_{2.5}$ density holding other things constant,[12] meaning that a one percent rise in plastic waste imports induces a 0.05 percent increase in $PM_{2.5}$ concentration. Alternatively, a city with an average annual growth rate of 50.2 percent in plastic waste imports would experience a rise in $PM_{2.5}$ density by 2.5 percent each year.

Notably, the first-stage estimation results, as shown in Table A.3 in Appendix A, indicate that our instrumental variable is a good predictor of city-level plastic waste imports. The high values of Klein-Paar F statistics of first-stage estimations as reported in Table 1 rule out a weak instrument problem. Notice that the 2SLS estimated coefficients on plastic waste imports are much larger than those of OLS estimations, indicating that the OLS results are underestimated.

The results on our control variables are generally consistent with existing studies and expectations. Interestingly, most socio-economic factors are not significantly correlated with air quality, except cities with a higher share of agricultural production in the local economy having better air quality. In contrast, we identify much stronger correlations with weather conditions. Temperature, precipitation, humidity, and wind speed are all negatively correlated with the $PM_{2.5}$ density.

[12] In a linear–arcsinh specification, the elasticity is: $\xi = \frac{\hat{\beta}}{\bar{y}} \frac{\bar{x}}{\sqrt{\bar{x}^2+1}}$, where $\hat{\beta}$ is the estimated coefficient of the independent variable, $\bar{x}$ is the mean of the independent variable, and $\bar{y}$ is the mean of the dependent variable (Bellemare and Wichman, 2020).

Table 1: Plastic waste imports and air quality: Baseline results

Dep. variable:	OLS			2SLS		
PM2.5 density	(1)	(2)	(3)	(4)	(5)	(6)
Pwaste imports (asinh)	0.168***	0.171***	0.154***	1.705***	1.805***	1.444***
	(0.041)	(0.041)	(0.038)	(0.227)	(0.235)	(0.211)
Population (ln)		0.244	0.538		-1.583	-1.097
		(2.613)	(2.496)		(2.461)	(2.251)
Employment (ln)		-0.810*	-0.829*		-0.632	-0.690
		(0.456)	(0.430)		(0.487)	(0.466)
GDP per capita (ln)		-0.599	0.422		0.342	1.282
		(1.056)	(0.940)		(1.361)	(1.171)
Primary sector output share (%)		-0.099**	-0.067*		-0.132**	-0.088*
		(0.044)	(0.039)		(0.054)	(0.048)
Secondary sector output share (%)		0.002	-0.002		0.011	0.006
		(0.007)	(0.006)		(0.010)	(0.007)
Average temperature (K)			-1.496***			-0.990***
			(0.206)			(0.264)
Precipitation rate (mm/hr)			-0.485*			-0.909***
			(0.257)			(0.334)
Average humidity (kg/kg)			-0.320***			-0.305***
			(0.044)			(0.049)
Wind speed west to east (m/s)			-0.102			-0.217**
			(0.087)			(0.096)
Wind speed south to north (m/s)			-1.530***			-1.282***
			(0.188)			(0.221)
First-stage KP F-statistics				374.628	318.750	331.962
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,869	3,869	3,869	3,869	3,869	3,869

Notes: This table reports OLS and 2SLS estimation results of Equation (1) using city-level data between 2000 and 2011 in columns (1) – (3) and (4) – (6), respectively. Dependent variable is average $PM_{2.5}$ density. Columns (4) – (6) use world total plastic waste exports times the probability of importing plastic waste of each city as the instrumental variable, as in Equation (2). Standard errors clustered at the city level are reported in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

4.2.2 Exploring possible channels

Plastic waste is imported mainly for the purpose of sorting out useful intermediate materials that can be re-used for production (Higashida and Managi, 2014; Kellenberg, 2015; Li et al., 2021). Due to a lack of efficient sorting and categorising technology, especially in the early years, sorting is predominantly finished by hand. Manual sorting can, however, filter out only a small portion of re-usable materials, while the overwhelming majority has to be disposed as waste

(Geyer et al., 2017). Non-recycled plastic waste is sent to landfills, incineration, or is dumped. Air pollutants can be generated during the processing of recycled plastic waste materials (the "production channel") and during the processing of non-recycled waste, particularly when plastics are incinerated (the "incineration channel").

While we are not able to detect air pollutants emitted by plastic waste processing firms directly, we hypothesise that plastic waste imports contribute to the expansion of the local waste processing industry. This is detrimental to local air quality due to increases in the emission of pollutants. At the same time, the expansion of the waste processing industry could contribute to local economic growth, which we capture with our control variables in the main estimation. To empirically examine this channel, we regress the size of waste processing production for each city on imported plastic waste. The size of waste processing production is measured by the total output of firms belonging to the non-metallic waste processing industry for each city.[13] Notice that data of the waste processing industry are only available since 2003, when China implemented a new industry classification, reducing our sample to the years 2003 to 2011.[14] Column (1) in Table 2 reports the 2SLS estimation result for the production size of waste processing industries using world export supply times the import probability for each city as the instrument. It shows that local plastic waste processing significantly expands with increasing plastic waste imports.[15]

While the annual survey data allow us to measure the production size of the waste processing industry, they do not cover below-scale private firms and small-sized individual businesses. Hence, they disregard production expansion due to the entry of small plants. To address this issue, we rely on an alternative firm registration dataset that covers the universe of firm registrations in China. We count the number of newly registered plastic waste processing firms for each city and regress it on city-level plastic waste imports.[16] Additionally, this data set allows for a distinction between ownership types, including state-owned enterprises (SOEs), private firms, and individual businesses. Columns $(2) - (5)$ in Table 2 report the results for the total number of plastic waste processing firms and the number by ownership. The impact on the total number of new plastic waste processing firms is positive, but is not statistically significant.

[13]Production data is aggregated from firm-level data collected by the ASIF that reports firm-level information for all state-owned enterprises and above-scale private firms.

[14]Output data is not available for 2010.

[15]Considering that imports of other waste products also affect the development of the waste processing industry, we replicate the same regression by adding imports of other waste. The results are very similar.

[16]We identify plastic waste processing firms relying on the description of each firm's registered business activities. We first constrain our sample to firms that belong to the waste processing industry and then select plastic waste processing firms based on the text describing their businesses. Firms with a keyword "*suliao*" or "*sujiao*" (both mean plastics) in their business descriptions are identified as plastic waste processing firms.

Table 2: Plastic waste imports, plastic waste production, and $PM_{2.5}$

Dep. var. (asinh):	Pwaste production	New entry of Pwaste plants				No. of fires
		Total	SOE	Private	Indi.	
	(1)	(2)	(3)	(4)	(5)	(6)
Pwaste imports (asinh)	0.698***	0.020	-0.011**	0.050***	0.024	0.148***
	(0.177)	(0.037)	(0.004)	(0.017)	(0.036)	(0.034)
First-stage KP F-statistics	175.947	331.962	331.962	331.962	331.962	331.962
City controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,583	3,869	3,869	3,869	3,869	3,869

Notes: This table reports 2SLS estimation results. Dependent variable is the output of the non-metallic waste processing industry (in log) in column (1), the number of newly registered plastic waste processing plants (total and by ownership, transformed by *asihn*) in columns (2)-(5), and the number of fires (transformed by *asihn*) in column (6), all measured at the city level. The instrumental variable for plastic waste imports is world total plastic waste exports multiplied by the average import propensity of each city defined as Equation (2) in all columns. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This is because of the offsetting results on SOEs and private firms. Specifically, imported plastic waste reduces the entry of SOEs but attracts more private firms to enter the market. In addition, the coefficient estimate for individual businesses is positive, albeit insignificant.

To examine the channel that affects air pollution through waste incineration, we rely on the data that record observable fires through satellite data. To this end, we count the number of fires in each city over the years 2000 to 2011 and regress it on plastic waste imports. While we are not able to identify the causes of fires, we expect that cities with more waste processing activities would observe more open-air fires, especially in rural areas. The result in column (6) in Table 2 confirms such an expectation and shows that plastic waste imports induce a higher number of fires.

As a further step to examine these possible channels, we regress the average $PM_{2.5}$ density on the channel variables. The results are set out in Table A.4. We fully acknowledge the endogeneity of the channel variables and only interpret the results as suggestive evidence. It shows that cities with more entries of private plastic waste processing firms have a significantly higher level of $PM_{2.5}$ density. In contrast, the size of plastic waste production, the number of plastic waste processing firm entries, and the number of entries of other types of firms are not significantly correlated to $PM_{2.5}$ density. Not surprisingly, the number of fires is highly correlated to $PM_{2.5}$ density, consistent with findings in existing literature (e.g. He et al., 2020; Guo, 2021).

The results in Table 2 and Table A.4 combined provide supportive evidence for both channels. Plastic waste imports seem to contribute to the expansion of local waste processing production and more entries of private waste processing firms. Further, we show that plastic waste imports increase open-air fires, leading to higher local $PM_{2.5}$ density.

4.2.3 Robustness checks

In this section, we examine our main findings by using alternative measures of $PM_{2.5}$, alternative instrumental variables, as well as specifications controlling for additional possible confounding factors.

Columns $(1) - (3)$ of Table 3 report the 2SLS estimation results using alternative measures of $PM_{2.5}$. Our main measure of $PM_{2.5}$ density is the average value of all pixels within a city. Alternatively, we use the minimum and the maximum value and report the baseline estimation results in columns (1) and (2), respectively. The estimated coefficients of plastic waste imports are very similar to the one of our preferred specification (column (6) of Table 1). Column (3) considers average $PM_{2.5}$ density calculated from pixel-level data provided by ACAG (Hammer et al., 2020). The coefficient estimate on plastic waste imports is positive and highly significant, with the coefficient size slightly smaller, supporting our main results based on the SEDAC data.

Columns $(4) - (6)$ report the 2SLS estimation results using alternative instrumental variables. In our main specification, we use the world total export supply of plastic waste multiplied by each city's import probability as the instrument. In column (4), we replace world total export supply with world total export of plastic waste to SEA countries, given that those countries are among the major recipients following China. In columns (5) and (6), we replace the probability of importing with the inverse of distance to the closest port, as in Equation (3), considering that cities further away from the port are less likely to import plastic waste. The first-stage results in Table A.3 show that all these three alternative instrumental variables are good predictors of actual plastic waste imports. The high values of F-statistics in Table 3 rule out problems of weak instrument. The second-stage results in Table 3 show positive and significant coefficients, supporting the main findings that plastic waste imports lead to higher $PM_{2.5}$ density.

Table 4 presents results by controlling for a series of additional control variables. Columns (1) and (2) report the results accounting for the role of other waste imports and total imports in general. This arises from the concern that China has been the main importer of other types of waste besides plastic waste, such as waste and scrap of rubber, paper, textile, and metallic materials. It is likely that cities that import plastic waste also import other types of waste,

Table 3: Plastic waste imports and air quality: Alternative $PM_{2.5}$ measures and instrumental variables

Dep. variable:	Alt. PM 2.5 measures			Alt. instrumental variables		
PM2.5 density	(1) Min.	(2) Max.	(3) ACAG	(4) Exp_SEA× Imp. Prob.	(5) Exp_WLD× Port Dist.	(6) Exp_SEA× Port Dist.
Pwaste imports (asinh)	1.406***	1.375***	0.802***	1.273***	3.494***	1.469***
	(0.195)	(0.229)	(0.205)	(0.190)	(0.522)	(0.252)
First-stage KP F-statistics	331.962	331.962	331.962	331.551	32.078	84.444
City controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,869	3,869	3,869	3,869	3,869	3,869

Notes: This table reports 2SLS estimation results of Equation (1) using alternative $PM_{2.5}$ measures (columns 1-3) and alternative instrumental variables (columns 4-6). Columns (1) and (2) use the maximum and the minimum value of $PM_{2.5}$ density of all pixels within a prefecture city as dependent variable. Column (3) uses the average $PM_{2.5}$ density retrieved from the Atmospheric Composition Analysis Group (ACAG) as dependent variable. The instrumental variable in column (4) is plastic waste exports to SEA countries multiplied by the average import propensity of each city. The instrumental variable in column (5) is world total plastic waste exports divided by the distance to the closest port. The instrumental variable in column (6) is world total plastic waste exports to Southeast Asian countries divided by the distance to the closest port. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with the latter often increasing air pollution as well. In column (1), we control for the imports of other types of waste at the city level. The identification of other types of waste relies on the list provided by OECD.Stat (2020). It includes waste and scrape products of chemicals, metals, minerals, papers, textile, and others, which covers 56 HS 6-digit codes. The estimation results show that imports of other types of solid waste do not affect average $PM_{2.5}$ density significantly. This may be because $PM_{2.5}$ is not the major pollutant emitted from processing those other types of solid waste. While they can contaminate the environment by emitting other types of pollutants, we are not able to empirically examine such effects due to data availability constraints. Controlling for the imports of other waste, the effect of plastic waste imports on local air pollution remains highly significant, highlighting the dominant role of plastic waste in affecting air quality.

Imports of other products could also affect the environment. Firms, in particular less productive ones, may adopt less costly but more pollution-intensive production technology in response to increased import competition, while larger and more productive firms may upgrade production technology and increase energy efficiency, which reduces pollutant emissions (Gutiérrez and Teshima, 2018; Cui et al., 2020). Improved access to cheaper intermediate inputs could

Table 4: Plastic waste imports and air quality: Additional controls and two-way clustering

Dep. variable: PM2.5 density	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pwaste imports (asinh)	1.470***	1.469***	1.467***	1.448***	1.402***	1.266***	1.266***
	(0.221)	(0.227)	(0.230)	(0.229)	(0.239)	(0.290)	(0.314)
Other waste imports (asinh)	-0.070	-0.070	-0.068	-0.065	-0.057	-0.055	-0.055
	(0.047)	(0.047)	(0.047)	(0.047)	(0.046)	(0.047)	(0.051)
Other imports (asinh)		0.006	0.007	0.010	0.005	0.015	0.015
		(0.097)	(0.097)	(0.097)	(0.097)	(0.096)	(0.102)
Plastic production (asinh)			0.061	0.056	0.057	0.061	0.061
			(0.044)	(0.044)	(0.045)	(0.045)	(0.049)
Plastic exports (asinh)			-0.020	-0.021	-0.024	-0.024	-0.024
			(0.044)	(0.044)	(0.044)	(0.043)	(0.060)
Pollution sector share (%)				-0.025	-0.027	-0.027	-0.027
				(0.018)	(0.018)	(0.018)	(0.018)
Fiscal expenditure p/c (ln)					1.415	1.519*	1.519
					(0.881)	(0.902)	(0.991)
Pwaste imports (asinh)$\times$ TCZ						0.231	0.231
						(0.229)	(0.251)
First-stage KP F-statistics	317.882	277.106	261.378	253.245	241.952	110.300	84.342
City controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	c	c	c	c	c	c	pt
Observations	3,869	3,869	3,869	3,869	3,811	3,811	3,811

Notes: This table reports 2SLS estimation results of Equation (1). Dependent variable is average $PM_{2.5}$ density. The instrumental variable for plastic waste imports is world total plastic waste export supply multiplied by the average import propensity of each city defined as Equation (2). Standard errors clustered at the city level in columns (1) − (6) and two-way clustered standard errors at the city level and the province-year level in column (7) are reported in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

also reduce pollution through raising production efficiency or substituting locally produced pollution-intensive inputs (Cherniwchan, 2017). Column (2) includes total imports net of waste imports as an additional control. The coefficient of other imports is negative but statistically insignificant. Controlling for the imports of both other types of waste and non-waste products does not change much the estimated impact of plastic waste imports on air quality.

In column (3), we consider possible effects related to local plastic production and exports. Local plastic production could affect our estimates in two ways. First, it is likely that cities with large plastic production, and hence with a high demand for plastic intermediate inputs, are more inclined to import plastic waste. It follows that part of the estimated effects of plastic waste imports on air quality can be attributed to plastic production. Second, plastic waste imports could help the expansion of local plastic production and subsequently the exports of plastic products since part of imported plastic waste can be used as the intermediate inputs for plastic production. While the expansion of the plastic production could contribute to local economic development, which may improve the environment quality, expanded production and exports of plastic products could cause environmental problems (Bombardini and Li, 2020; Wang, 2021). We address the role of local plastic production by adding the total output of the plastic industry and total exports of plastic products in the regression. City-level data on the output of the plastic industry are calculated from the ASIF data. City-level export data on plastic products are from the customs data. The estimation results in column (3) show that neither plastic production nor plastic exports significantly impact air quality. Conditional on plastic production, the estimated effects of plastic waste imports remain virtually the same.

An additional concern is related to the size of local pollution-intensive production. It is possible that cities with a higher share of pollution-intensive production have laxer enforcement of environmental regulations and are more likely to import plastic waste. We address such a possibility by including the share of pollution-intensive production in our estimation. Pollution-intensive industries are ones that emitted industrial smoke above the average in 2000. The production share is calculated again using the ASIF data. The results in column (4), however, do not show evidence that pollution-intensive production is significantly correlated to air quality. We continue to find a positive and highly significant coefficient on plastic waste imports.

In columns (5) and (6), we directly test the possible confounding effects of environmental policies and the local government's capability of protecting the environment. We do so first by including local government's fiscal expenditure per capita in column (5) assuming that governments with higher fiscal expenditures are more likely to invest more on environmental protection. Column (6) includes a dummy variable indicating whether a city belongs to the Two Control Zone (TCZ), which is an environmental policy implemented since the late 1990s that aims to reduce the emission of SO_2 and acid rain in selected regions. Adding these two additional variables does not affect the main results much, though the size of the effect of plastic waste imports reduces slightly.

In column (7), we check the robustness of our results by clustering the standard errors at the city and the province-year level. This arises from the concern of possible spillover effects of air pollution across regions. Clustering standard errors at the province-year level essentially allows for correlation between cities within provinces in a specific year. As shown in column (7), the estimated coefficient of plastic waste imports remains unchanged with two-way clustered standard errors.

Lastly, we test the timing of the effects by lagging the plastic waste import measure by one year. While we believe that the majority of imported plastic waste is processed within the imported year, we cannot rule out the possibility that a large bulk of imports require a longer time to process, thereby creating lagged effects on air pollution. We report the results in Table A.5 in Appendix A, in which columns (1) and (2) correspond to estimations using $PM_{2.5}$ calculated from the SEDAC data and the ACAG data, respectively. The estimated coefficients on plastic waste imports are positive and highly significant, with the magnitude being slightly smaller than the ones obtained using the contemporary measure.

5 The effect of the plastic waste import ban on air quality: 2015-2020

With the rising concerns about environmental problems, the Chinese government introduced a ban on the imports of plastic waste materials that entered into force in January 2018. In this section, we empirically evaluate whether the ban has improved air quality using daily data on air pollutants at the monitoring station level between 2015 and 2020.

5.1 Empirical strategy and identification issues: DiD specification

To estimate the effect of the plastic waste import ban on air quality, we use a DiD approach. Specifically, we compare the level of air pollution between cities that are affected by the ban and those not before and after the ban. As mentioned earlier, we do not have data that allow us to observe city-level imports of plastic waste right before the ban. To identify cities that are potentially affected by the ban, we rely on our data for earlier years and consider cities that imported plastic waste between 2000 and 2011 as treatment cities. In the robustness checks, we consider alternative definitions. The empirical specification is as follows:

$$PM_{2.5,scd} = \beta Pwaste\ importer_c \times Ban_d + \gamma Weather_{cd} + \theta_d + \mu_{s,day} + \varepsilon_{scd}, \tag{4}$$

where $PM_{2.5,scd}$ denotes the average $PM_{2.5}$ density recorded by monitoring station s in city c on date d. $Pwaste\ importer_c$ is a dummy variable indicating cities that imported any plastic waste in the years $2000 - 2011$, and Ban_d denotes dates post the implementation of the plastic waste import ban. The coefficient of the interaction term, β, measures the effect of the import ban on $PM_{2.5}$ concentration. Considering that China announced the import ban to the WTO in July 2017 and that China implemented a second ban in December 2018, which banned the imports of all remaining types of plastic waste materials, we include additional time indicators denoting the dates post these two events as robustness checks.

Similar to Equation (1), we control for a set of measures of weather conditions at the city level. Those variables include temperature, precipitation, humidity, and wind speed, all measured at a daily basis. In addition, we include date fixed effects (θ_d) to account for common shocks to all stations each day and station times day of the year fixed effects ($\mu_{s,day}$) to allow for location-specific seasonality. As such, the identification of the effect of the ban derives from variations in air pollution recorded by the same monitoring station on the same day of different years. ε_{scd} is the error term. We cluster standard errors at the city level to allow for possible correlations within cities.

The DiD approach rests on the assumption that the control and treatment groups follow a parallel trend before the implementation of the policy. To check this assumption, we plot daily time trends in $PM_{2.5}$ density separately for plastic waste importing and non-importing cities in Figure A.5 and monthly trends in Figure A.6 in Appendix A. In both figures, the left graph depicts the unconditional trend, whereas the right graph shows the conditional $PM_{2.5}$ trend that controls for seasonality.[17] Both figures show that $PM_{2.5}$ levels are highly fluctuated across time, with a higher level in winter months, most likely due to heating in northern China (Ebenstein et al., 2017). Consistent with Figure A.2, average $PM_{2.5}$ density shows a decreasing trend in both types of cities over time. Plastic waste importing cities have, in general, slightly higher $PM_{2.5}$ levels as compared to cities that did not import plastic waste prior to the introduction of the ban, whereas the difference shrinks post the ban. Controlling for seasonality, average $PM_{2.5}$ density in plastic waste importing cities even falls below non-importing cities, showing descriptively supportive evidence that air quality improves following the ban. Notably, the two types of cities do not show differential trends during the pre-ban period, suggesting that the parallel trend assumption is satisfied. In Section 5.2.1, we test the parallel trend assumption more rigorously in an event study design.

5.2 Empirical results

5.2.1 The DiD estimation results and identification concerns

Table 5 reports the estimation results of Equation (4). Column (1) corresponds to the specification including weather controls, station fixed effects, and date fixed effects. Column (2) replaces

[17] We control for seasonality by including day or month fixed effects in estimations and plot the residuals.

station fixed effects with station times day of the year fixed effects, the latter controlling for station-specific seasonality. In both specifications, the coefficient of the interaction term is negative and statistically significant, indicating that plastic waste importing cities on average experience a reduction in $PM_{2.5}$ density following the ban relative to non-importing cities. Controlling for station-specific seasonality in column (2), the magnitude of the coefficient increases. It shows that $PM_{2.5}$ concentration decreases by 3.7 $\mu g/m^3$ on average with the implementation of the import ban in plastic waste importing cities. This corresponds to 8.5 percent of the average level between 2015 and 2020 (see Table A.2).

Table 5: Plastic waste import ban and $PM_{2.5}$: DiD estimation results

Dep. variable: PM2.5 density	(1)	(2)
Pwaste importer×Ban	-2.976***	-3.683***
	(0.978)	(0.988)
Weather controls	Yes	Yes
Date FE	Yes	Yes
Station FE	Yes	No
Station×Day of year FE	No	Yes
Observations	2,933,330	2,933,330
R^2	0.463	0.622

Notes: This table reports the OLS estimation results of Equation (4). Dependent variable is the daily $PM_{2.5}$ density recorded by each monitoring station. Column (1) includes station fixed effects and date fixed effects. Column (2) includes station times day of the year fixed effects and date fixed effects. Both specifications control for weather conditions including temperature, precipitation, humidity, and wind speed. Standard errors clustered at the city level are reported in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

To further validate the common trend assumption of the DiD estimation, we conduct an event study by including a set of lags and leads:

$$\begin{aligned} PM_{2.5scd} = & \sum_{m=-1}^{-7} \beta_m Pwaste\ importer_c \times D_m + \sum_{n=1}^{11} \beta_n Pwaste\ importer_c \times D_n \\ & + \gamma Weather_{cd} + \theta_d + \mu_{s,day} + \varepsilon_{scd}, \end{aligned} \tag{5}$$

where D_m is a dummy for m months before the ban, and D_n is a dummy for n months after the ban. In particular, D_{-7} indicates all months up to June 2017, and D_{11} indicates all months in December 2018 and onward. The reference group is the month of the ban, i.e. January 2018. The coefficient of the interaction terms, β, measures the difference in $PM_{2.5}$ density between plastic waste importing and non-importing cities in that month relative to the average difference in January 2018 conditional on a full set of control variables and fixed effects. Figure 3 presents the full series of coefficient estimates of the interaction terms and the corresponding 95 percent confidence intervals. All pre-treatment estimated differences are statistically insignificant from zero, reassuring us that the treatment and control cities did not have systematic differences in $PM_{2.5}$ density before the ban. Notably, we do not find significant differences between the two types of cities around the time of China's announcement to the WTO in July 2017. This rules out possible anticipation effects of the policy change. The post-treatment estimates show that three months after the policy implementation, $PM_{2.5}$ concentration is significantly lower in plastic waste importing cities as compared to non-importing ones and remains at a roughly same level over time. The insignificant estimates for February and March 2018 could be explained by the fact that the vast amount of plastic waste may take time to be processed, which still produced air pollution. Overall, the dynamics over time in Figure 3 confirm the validity of our DiD identification strategy and reassure a causal interpretation of the estimated effects.

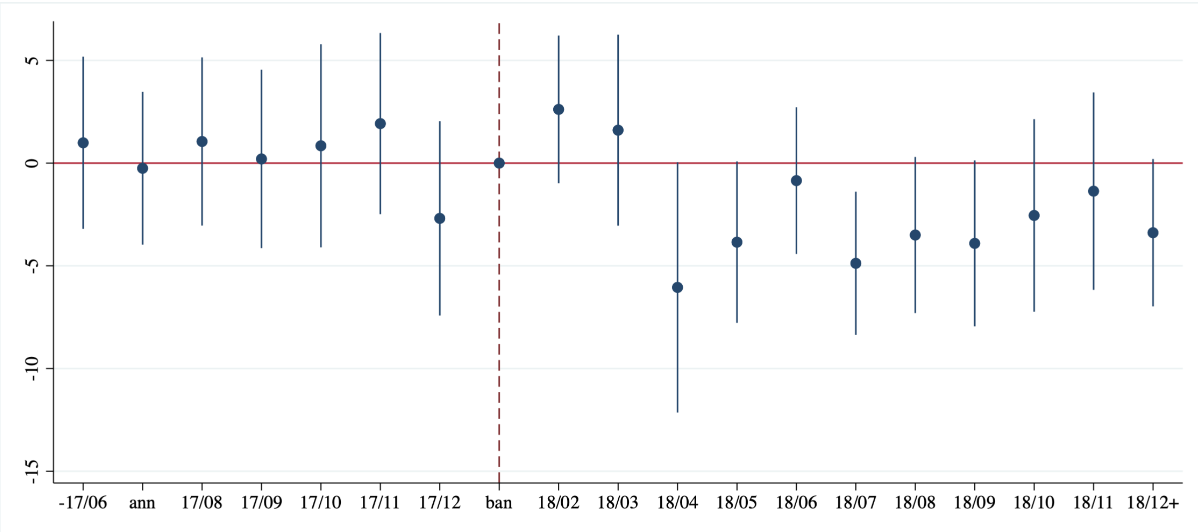


Figure 3: Plastic waste import ban and $PM_{2.5}$: Event study

Notes: This figure shows a full set of coefficient estimates of the interaction terms in Equation (5) and the corresponding 95 percent confidence intervals. All coefficients are measured relative to the treatment month (January 2018). The left endpoint indicates months up to June 2017, and the right endpoint indicates months in December 2018 and onward. The regression includes a full set of weather conditions, date fixed effects, as well as station times day of the year fixed effects. Standard errors are clustered at the city level.

In Table 6, we assess possible confounding effects of other policies related to waste imports that were implemented during our sample period. The first concern is again related to the possible anticipation effects of the import ban due to China's announcement of the ban to the WTO around half a year before implementation. It could be the case that the announcement of the ban initiated a reduction in plastic waste imports, resulting in improved air quality already before the implementation of the ban. As shown in Figure 3, we do not find a clear difference in $PM_{2.5}$ density between plastic waste importing and non-importing cities around the time of announcement. We test this possibility again in column (1) of Table 6 by interacting plastic waste importing cities with a post announcement dummy. The coefficient of the interaction

Table 6: Plastic waste import ban and $PM_{2.5}$ in 2015-2020: Possible effects of other policies

Dep. variable: PM2.5 density	(1)	(2)	(3)	(4)
Pwaste importers×Ban	-3.549***	-3.303***	-3.405***	-2.921***
	(1.010)	(0.986)	(0.892)	(0.903)
Pwaste importers×Announcement	-0.157			-0.178
	(0.932)			(0.932)
Other waste importers×Contamination limit		-0.767		-0.762
		(0.640)		(0.639)
Pwaste importers×Second ban			-0.434	-0.364
			(0.726)	(0.721)
Weather controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Station×Day of year FE	Yes	Yes	Yes	Yes
Observations	2,933,330	2,933,330	2,933,330	2,933,330
R^2	0.622	0.622	0.622	0.622

Notes: This table reports OLS estimation results of Equation (4) by including other relevant policies. Announcement is a dummy variable indicating the time after China's announcement to the WTO in July 2017 about its ban on plastic waste imports. Contamination limit indicates the time after China tightened the contamination of other waste imports in March 2018. Second ban indicates the time after January 2019 when China implemented the second ban on plastic waste imports. Pwaste importers indicate cities that imported plastic waste imports between 2000 and 2011. Other waste importers are those that imported any other types of waste between 2000 and 2011. All regressions include a full set of weather controls as in Table 5, date fixed effects, as well as station times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

term is negative but statistically insignificant. Controlling for possible expectation effects, the impact of the ban becomes smaller, but remains significant.

The second policy that we consider is the regulation implemented in March 2018 that aims to reduce waste contamination by tightening the share of contamination of all types of solid waste imports, including plastic waste that was not banned in January. Figure 3 shows a clear drop in relative $PM_{2.5}$ density in April 2018, which could be the impact of this policy. To address this possibility, we include an interaction term between other waste importers and a time dummy indicating March 2018 onward in column (2). Other waste importers are cities that imported any type of waste between 2000 and 2011. We find a negative coefficient but it is statistically insignificant. Controlling for the possible effects of the contamination limit regulation does not alter much the coefficient estimate of the ban.

In column (3), we consider the second plastic waste import ban effective on December 31, 2018, which mainly aims to ban plastic waste from industrial production. Indeed, China's imported plastic waste was reduced immediately following the first ban and imported only a small amount in 2018 (see Figure 1). We thereby do not expect a strong impact of the second ban. This is confirmed by the insignificant coefficient in column (3).

Column (4) controls for all the above three policies. Similar to columns (1) to (3), we do not find evidence that any of the policies affect air quality significantly. The air quality improving effect of the first ban is still significant.

A further concern is related to the possible imprecise identification of treatment cities due to a lack of data on plastic waste imports at the city level between 2015 and 2020. In the main analysis, we rely on historical importing records and define treatment cities as those importing plastic waste in any year between 2000 and 2011. Yet, if, for instance, cities importing plastic waste in earlier years were aware of the negative environmental impact and stopped importing, they would not be affected by the import ban and should be treated as control cities. We test the sensitivity of our results by considering alternative identification strategies and report the results in Table 7.

In column (1), we replace the plastic waste importer dummy with a continuous measure defined as the probability of importing plastic waste, calculated as the share of years for which each city imported plastic waste between 2000 and 2011. The underlying assumption is that importing activities are persistent, such that cities with a longer history of plastic waste importing activities are more likely to import plastic waste in later years. Columns (2) and (3) are based on the same assumption and limit the treatment group to cities with a relatively long history of plastic waste importing activities. Specifically, we define cities that imported plastic waste for at least four years during $2000 - 2011$, the median length of import history, as treatment cities in column (2), and cities that imported plastic waste for at least six years, corresponding to an importing probability of 50% or above, as treatment cities in column (3).

In column (4), we define treatment cities based on their imports in 2011, the latest year for which we have data on plastic waste imports. Cities that imported plastic waste in 2011 are classified into the treatment group, relying on the assumption that cities importing plastic waste in 2011 are more likely to import before the ban than those that imported plastic waste only in earlier years.[18] In all four specifications, we estimate adverse and statistically significant effects of the ban on air quality, providing assuring evidence to our main finding that the plastic waste import ban improves air quality.

[18]The number of cities that imported plastic waste for four years and six years during 2000-2011, and in 2011 is 184, 131, and 200, respectively.

Table 7: Plastic waste import ban and $PM_{2.5}$ density in 2015-2020: Alternative definitions of plastic waste importing cities

Dep. variable: PM2.5 density	(1)	(2)	(3)	(4)
Pwaste import probability$\times$Ban	-2.918***			
	(0.991)			
Pwaste importer (Median length)$\times$Ban		-2.522***		
		(0.681)		
Pwaste importer (Prob$\geq$50%)$\times$Ban			-1.947***	
			(0.702)	
Pwaste importer (in 2011)$\times$Ban				-2.222***
				(0.676)
Weather controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Station$\times$ Day of year FE	Yes	Yes	Yes	Yes
Observations	2,933,330	2,933,330	2,933,330	2,933,330
R^2	0.622	0.622	0.622	0.622

Notes: This table reports OLS estimation results of Equation (4) with alternative definitions of treatment cities. Column (1) uses the probability of importing plastic waste defined as the share of years when a city imported plastic waste between 2000 and 2011. Columns (2) and (3) define treatment cities as those that imported plastic waste for at least four years (the median import length) and six years (an importing probability of 50%) between 2000 and 2011, respectively. Column (4) defines treatment cities as those importing plastic waste in 2011. All regressions include a full set of weather controls as in Table 5, date fixed effects and station times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

As an additional check of the sensitivity to the selection of treated cities, we perform a falsification test and estimate Equation (4) based on randomly selected treatment cities following e.g. La Ferrara et al. (2012) and Wang et al. (2021). Specifically, we randomly select 275 treatment cities and the timing of the ban, and generate a placebo treatment variable. The randomly assigned treatment should, on average, show no significant impact on air quality, if differences in $PM_{2.5}$ concentrations are caused by the introduction of the ban. We repeat the estimation of Equation (4) using the placebo treatment variable 500 times and plot the density distribution of the estimated coefficients in Figure 4. It shows a normal distribution centred around 0 with a mean of 0.027, and our benchmark estimate (column (4) of Table 5) lies in the far left, which is a clear outlier. This further confirms that our main estimate is unlikely biased.

5.2.2 Additional robustness checks

In this section, we examine the sensitivity of our main findings to alternative model specifications, clustered standard errors at different levels, additional measures of air pollution, as well as estimations at the city level.

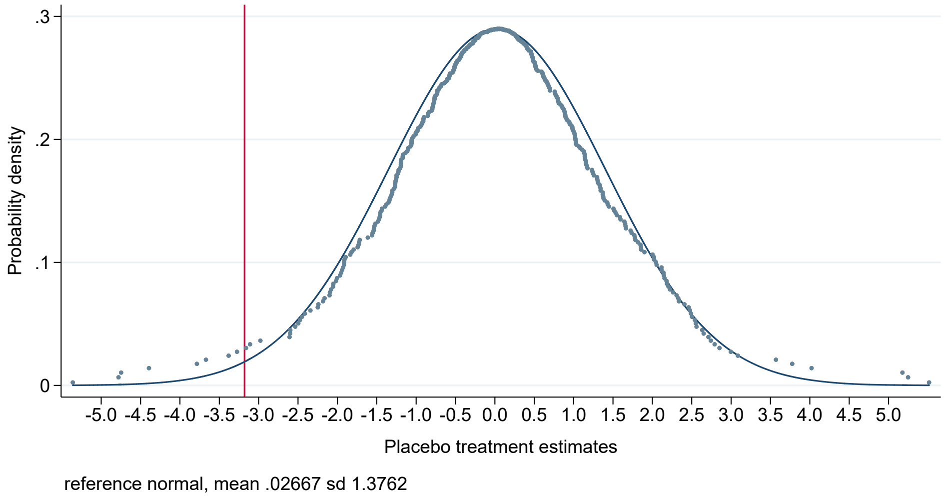


Figure 4: Distribution of estimated coefficients using the placebo policy variable

Notes: The figure shows the density distribution of the coefficient estimates from a simulation of 500 regressions of Equation (4) in which treatment cities and the policy timing are randomly selected. The red line marks the benchmark treatment effect.

In columns $(1)-(4)$ of Table 8, we present the results of estimations allowing cities or stations to follow differential time trends. This addresses the concern that treatment and control cities may not follow a completely parallel trend. As shown in Figure 3, treatment and control cities do not show statistical differences in average $PM_{2.5}$ density before the ban, but do show a slightly increasing trend since China's announcement of the ban to the WTO and a reduction in December 2017. In column (1), we add a city-specific linear time trend, and in column (2) we include a station-specific linear trend. Column (3) adds a quadratic time trend at the station level, and column (4) allows stations to follow various time trends up to polynomial degree four. Throughout all regression specifications, the estimated coefficient remains statistically significant and negative. Yet, these demanding specifications reduce the magnitude of the effect by around half.

We cluster the standard errors at the city level in our main analysis to allow for possible correlations between monitoring stations within cities. This also allows for serial correlations over time for each city. However, correlations at a more aggregate level, for instance, at the province level, are plausible due to spatial spillovers or environmental policies at a higher administrative level. We investigate whether this influences our main findings by clustering the standard errors at different levels. Specifically, we re-estimate our preferred specification as in column (4) of Table 5 but cluster the standard errors at the province level in column (5) of Table 8. In column (6), we consider a two-way clustering approach at both the city and province-year levels. This essentially allows for correlations within cities but also possible correlations across cities within provinces each year. The results show that clustering the standard errors at different levels does not affect the significance of the coefficient much.

Table 8: Plastic waste import ban and $PM_{2.5}$ density in 2015-2020: Controlling for time trends and clustering standard errors at different levels

Dep. variable:	Time trend				SE clustering	
PM 2.5 density	City	Station	Station	Station	Province	Two-way
	(1)	(2)	(3)	(4)	(5)	(6)
Pwaste importers × Ban	-2.073**	-2.091**	-1.943**	-1.972**	-3.683***	-3.683***
	(0.889)	(0.893)	(0.869)	(0.875)	(1.194)	(1.075)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Station × Day of year FE	Yes	Yes	Yes	Yes	Yes	Yes
City time trend	Yes	No	No	No	No	No
Station time trend	No	Yes	Yes	Yes	No	No
Station quadratic time trend	No	No	Yes	Yes	No	No
Higher-level station time trends	No	No	No	Yes	No	No
Observations	2,933,330	2,933,330	2,933,330	2,933,330	2,933,330	2,933,330
R^2	0.629	0.631	0.636	0.636	0.622	0.622

Notes: This table reports OLS estimation results of Equation (4) by including city- and station-specific time trends (columns 1-4) and clustering standard errors at different levels (columns 5-6). Estimation sample includes daily data for the years 2015-2020. All specifications include a full set of weather controls, date fixed effects, and station times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses in columns $(1)-(4)$. Standard errors clustered at the province level are in parentheses in column (5). Two-way clustered standard errors at the city level and the province-year level are in column (6). * p <0.1, ** p <0.05, *** p <0.01.

In this paper, we use $PM_{2.5}$ as the primary measure of air pollution mainly due to data constraints, especially for the earlier years. Existing studies suggest that incineration, degradation and processing of plastic waste do not only release fine particles in the air but also increase the concentration of carbon monoxide, larger particulate matters and other pollutants (Verma et al., 2016). The CNEMC reports data on six specific types of pollutants from 2014 and a composite air quality index calculated based on the six pollutants.

In Table 9, we investigate the effects of the plastic waste import ban on other air quality measures. We start from the composite air quality index (AQI) in column (1). It ranks the air quality around each monitoring station on a scale from 0 (very good) to 500 (very bad) based on ozone, carbon monoxide, particulate matters ($PM_{2.5}$ and PM_{10}), nitrogen and sulphur dioxide concentrations. As expected, we find a negative, statistically significant coefficient on the interaction term. Thus, overall air quality in cities that imported plastic waste in the past improved after the ban relative to other cities. Columns (2) to (6) report coefficient estimates on the five additional individual air pollutants, respectively. The results show that the plastic waste import ban also significantly reduced the emission of sulphur dioxide, nitrogen dioxide, and PM_{10}, which are among the

Table 9: Plastic waste import ban and air pollution in 2015-2020: Alternative measures of air pollution

Dep. variable:	AQI	CO	O_3	SO_2	NO_2	PM_{10}
As in column title	(1)	(2)	(3)	(4)	(5)	(6)
Pwaste importers×Ban	-3.643***	-0.022	2.233**	-3.708**	-1.913***	-6.361***
	(1.043)	(0.030)	(1.109)	(1.436)	(0.567)	(1.683)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Station×Day of year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,930,644	2,930,539	2,930,789	2,930,796	2,930,799	2,928,752
R^2	0.617	0.576	0.670	0.600	0.712	0.555

Notes: This table reports OLS estimation results of Equation (4) using alternative air pollution measures, as shown in column titles. All regressions include a full set of weather controls, date fixed effects, and station times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

major pollutants resulting from plastic incineration. We do not find statistically significant effect on the concentration of carbon monoxide in the air but a significant and positive effect on ground-level ozone concentration. This latter positive effect on ozone may be attributed to the fact that ground-level ozone is not emitted directly but involves a complex chemical reaction process of nitrogen oxides (NOx) with volatile organic compounds (VOCs) with the presence of sunlight.[19] The results in Table 9 provide evidence that the plastic waste import ban can improve air quality by reducing the emission of various additional pollutants.

The outcome variable of our main specification is measured at the monitoring station level, whereas the treatment is identified at the city level. If monitoring stations are not located randomly, especially if monitoring stations are located strategically in locations with worse air quality and these locations are close to plastic waste processing productions, our estimates would be biased. An additional concern is that cities have an uneven number of monitoring stations, such that cities with a larger number of stations weigh more in the estimation. To address these concerns, we average $PM_{2.5}$ densities over all stations for each city for each date and run our preferred regression model at the city level, controlling for a full set of weather

[19] Using a similar DiD approach, Li and Takeuchi (2021) find that the plastic waste import ban reduced ground-level ozone in China. To understand the different findings, we add nitrogen dioxide as an additional control to account for the fact that ozone formation requires nitrogen oxides and constrain our sample period to 2017-2018 following their approach. We find a negative, statistically insignificantly coefficient. The main reason for the different findings could be the different sample coverage. Li and Takeuchi (2021) define treatment cities as all cities in Shandong, Zhejiang, and Guangdong provinces and control cities in Sichuan, Hubei, and Hunan provinces, amounting to 90 cities, in contrast to our sample including all Chinese prefecture-level cities. Restricting the estimation sample to the years 2017-2018, we continue to find highly significant and negative impacts on $PM_{2.5}$, PM_{10}, SO_2, and the AQI index.

conditions. The results are set out in Table A.6 in Appendix A, where column (1) includes date fixed effects and city fixed effects and column (2) replaces city fixed effects with city times day of the year fixed effects. Both specifications present a negative, highly significant coefficient of the interaction term, suggesting that plastic waste importers experienced a reduction in $PM_{2.5}$ density following the ban compared to other cities. The magnitude of the effect is comparable to our baseline result using station-level data.

5.3 Channel analysis

In Section 4.2.2, we find that plastic waste imports raise $PM_{2.5}$ density through expanded production of the plastic waste processing sector and an increased number of incineration. With the introduction of the import ban, we would expect reverse effects: a contraction of the plastic waste processing sector and a reduced number of incineration, which then contribute to improved air quality. Unfortunately, we do not have data on the output of the waste processing industry for the years $2015 - 2020$. We, therefore, examine changes in the number of newly registered plastic waste processing plants and those in the number of fires. As data on the number of new plant registration are only available at a yearly frequency, we examine this channel by running regressions at the city-year level. Analogous to Table 2, we regress the total number of new plastic waste processing plants and the number by ownership type, all transformed by *asinh*, on the plastic waste importer indicator times the post ban dummy. The results are set out in Table A.7 in Appendix A. Contrary to our expectation, firm registrations in previous plastic waste importing cities increased relative to non-importers following the ban, particularly the number of private firms (columns $1 - 4$).

To examine whether the increased number of plastic waste processing plants is correlated to changes in $PM_{2.5}$ density, we regress the average $PM_{2.5}$ density at the city level on the number of plant registrations and the results are reported in columns $(5) - (8)$. We do not find any significant correlations, neither with the total number nor the number by ownership. The results combined suggest that changes in the size of the waste processing sector are not a channel explaining the air quality improving effects of the plastic waste import ban.

To analyze the "incineration channel", we estimate Equation (4) by using the number of fires (in *asinh*) as the dependent variable. As the number of fires is only observed at the city level instead of the station level, we replace station times day of the year fixed effects with city times day of the year fixed effects. We find negative coefficients of the policy but significant only when we use the probability of importing plastic waste as the treatment variable, as shown in columns (1) and (2) of Table A.8 in Appendix A. In column (3), we regress the average $PM_{2.5}$

density on the number of fires (in *asinh*) and find that cities with a larger number of fires have a higher $PM_{2.5}$ concentration. This set of results indicates that the reduction of incineration could potentially be a channel that explains the positive impact of the ban on air quality.

6 Concluding remarks

With the wide use of plastics in industrial production and daily life, global plastic waste production has been rocketing in the past decades. Subsequently, global plastic waste trade has experienced a rapid increase, more than 12 times the amount of 1996 as of 2011, largely due to shipments from developed to developing countries. Before 2018, China was the major destination of plastic waste shipment, receiving almost half of global plastic waste exports each year in the early 2010s. Recognising the possible harm to the environment, China has permanently banned the import of non-industrial plastic waste since January 2018 and the import of all other types of plastic waste since December 2018. Using data spanning the period 2000 to 2020, this paper examines the causal impact of plastic waste imports on air pollution and evaluates the effect of the plastic waste import ban on air quality.

To examine the environmental effects of plastic waste imports, we focus on the $2000 - 2011$ period, when China experienced a drastic increase in plastic waste imports. Exploring the temporal and geographical variations using city-level data on plastic waste imports, which are then linked to data on $PM_{2.5}$ density, we specifically investigate whether cities importing more plastic waste have a higher $PM_{2.5}$ density. To solve the endogeneity problem, we construct two alternative instrumental variables for city's imports of plastic waste by combining exogenous variation in world total export supply of plastic waste over time with the probability of importing for each city or with the distance of each city to the closest port. We find strong and robust evidence that plastic waste imports increased the average $PM_{2.5}$ density in importing cities. Such an impact is linked to the import induced expansion in waste processing production and an increased number of open-air incineration.

As a second step, we evaluate the effects of the plastic waste import ban on air quality using a DiD estimation approach. Relying on daily data on various air quality measures between 2015 and 2020, we find that cities that previously imported plastic waste experienced significant improvement in air quality following the ban compared to other cities. This finding is robust to a rich set of robustness checks and validation exercises. We also find that the ban reduced the number of fires, which contributed to the reduction in pollutant emissions.

This paper focuses on air pollution, a major determinant of climate change, poor health and premature death (Fan et al., 2020; Bombardini and Li, 2020; He et al., 2020; Deschenes et al., 2020). Air pollution also affects economic development by reducing productivity (Fu et al., 2021, 2022), increasing crime (Bondy et al., 2020), and leading to emigration (Chen et al., 2021). Our results that plastic waste imports significantly increase air pollution imply that there may be further effects on additional socio-economic outcomes. The import ban on plastic waste, on the other hand, could have additional benefits beyond air quality improvement.

As a vast majority of non-recycled plastic waste ends up in landfills, dumps, or the natural environment, inappropriate processing of plastic waste could also cause serious microplastic contamination on land (Chae and An, 2018) and plastic pollution in the ocean (Jambeck et al., 2015; IUCN, 2021), which further threatens food safety, health, and the entire ecosystem. The findings in this paper imply that plastic waste imports by developing countries like China where solid waste management technology is less developed could not only bring about air pollution, but could also result in pollution to the soil, river, and the ocean. Existing studies find that China is the largest source of marine plastic pollution (Jambeck et al., 2015). This is admittedly related to its own production of plastic waste. Imported plastic waste, however, accounting for more than 10% additional mass in China (Brooks et al., 2018), also plays a crucial role.

Following China's plastic waste import ban, global plastic waste shipments were quickly redirected to South and Southeast Asian countries, such as Malaysia, Thailand, and India (Brooks et al., 2018, also see Figure 1). In recent years, some of those countries have also implemented or have a plan to implement a similar ban. With rising concerns over the global environmental problems brought about by the rapidly rising amount of plastic waste, 187 countries reached an international agreement in 2019, the *Basel Convention*, which became effective in January 2021, to restrict international trade in plastic waste (UNEP, 2019). In the meantime, several countries, including the EU and Australia, have enacted new laws that ban the exports of plastic waste. The findings in our paper provide quantitative evidence supporting those regulations in other countries. Questions regarding the environmental consequences in previous large plastic waste exporters following the ban and developing a sustainable way to manage plastic waste domestically in the long run still remain.

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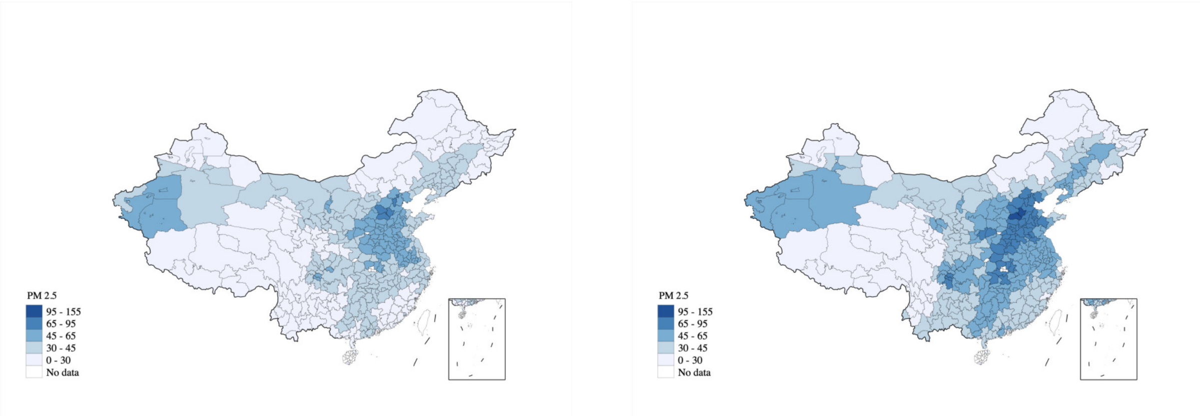
Appendix A Additional figures and tables



(a) 2000 (b) 2011

Figure A.1: $PM_{2.5}$ density by city based on the ACAG data in 2000 and 2011

Notes: This map shows city-level average $PM_{2.5}$ density in 2000 and 2011. Data on average $PM_{2.5}$ are retrieved from the Atmospheric Composition Analysis Group (ACAG) (Hammer et al., 2020).

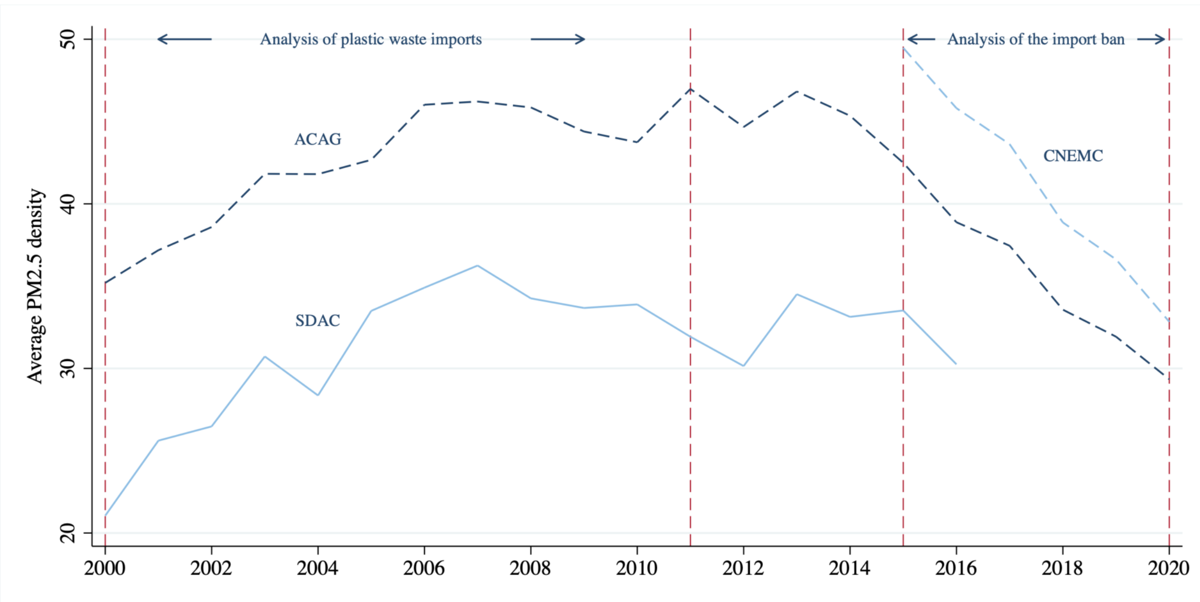


Figure A.2: Average $PM_{2.5}$ density over time: 2000-2020

Notes: This figure shows the time trend of average $PM_{2.5}$ density based on data from three sources. SEDAC denotes the Socialeconomic Data and Applications Center at Columbia University (Center for International Earth Science Information Network - CIESIN - Columbia University, 2020), which provides yearly pixel-level $PM_{2.5}$ estimates from 2000 to 2016. ACAG denotes the Atmospheric Composition Analysis Group (ACAG) (Hammer et al., 2020), which provides yearly pixel-level $PM_{2.5}$ estimates from 2000 to 2020. CNEMC denotes the China National Environmental Monitoring Centering, which provides daily station-level $PM_{2.5}$ data from 13 May, 2014.

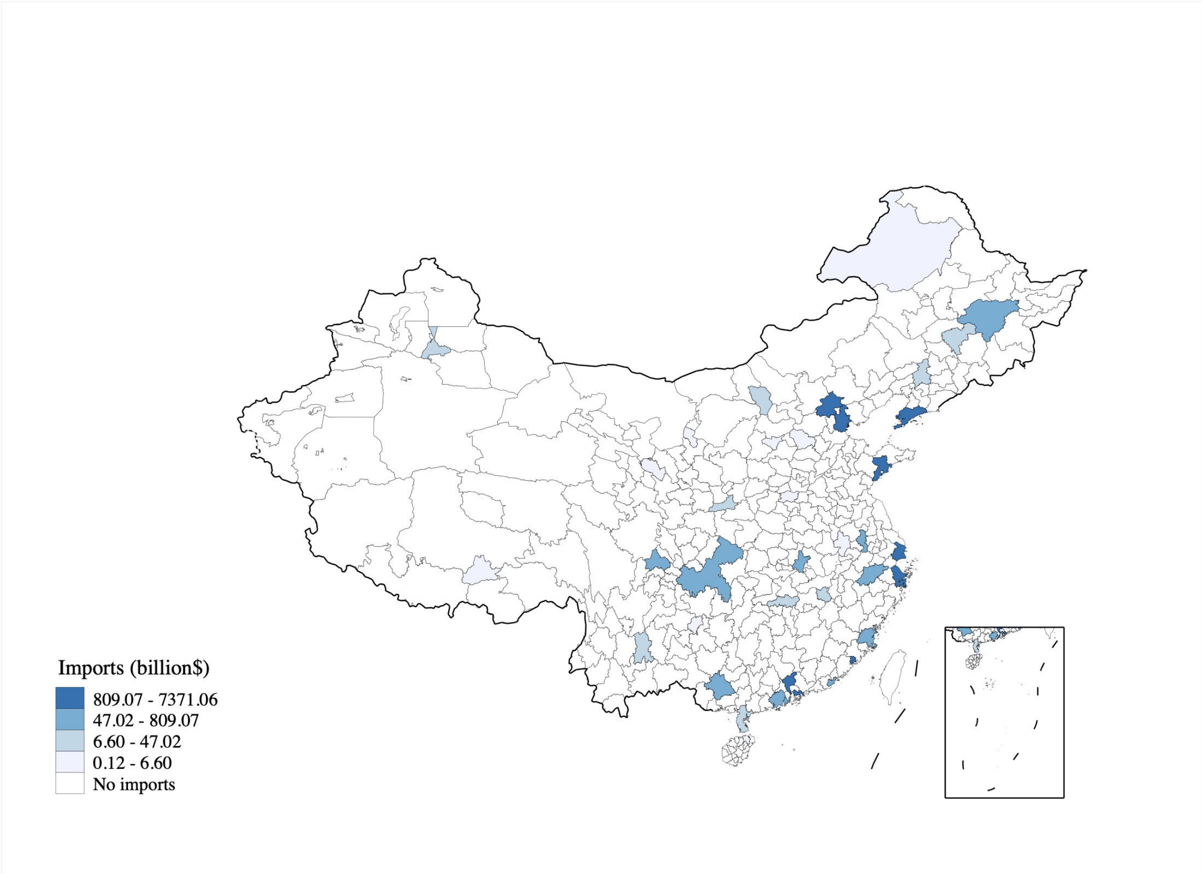
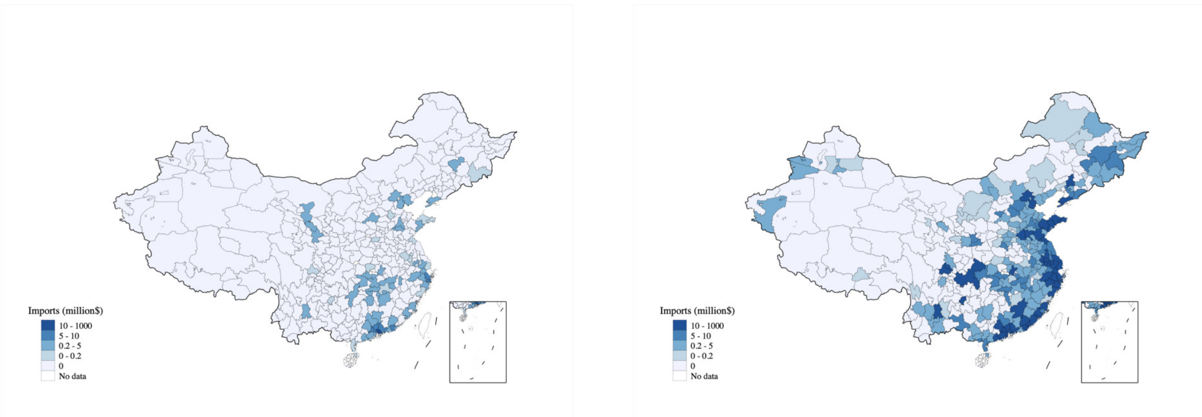


Figure A.3: Total plastic waste imports by entry city between 2000 and 2011

Notes: This map shows total value (in billion US dollar) of plastic waste imports by entry city between 2000 and 2011. Entry city indicates a city where imported waste products were first unloaded from cross-border means of transport. Data are retrieved from China customs data. Plastic waste products are identified according to HS8 codes 39151000, 39152000, 39153000, 39159010, and 39159090.



(a) 2000 (b) 2011

Figure A.4: Plastic waste imports by city in 2000 and 2011

Notes: The maps show city-level imports of plastic wastes (in million USD) in 2000 and 2011. Data are retrieved from China customs data. Plastic waste products are identified according to HS8 codes 39151000, 39152000, 39153000, 39159010, and 39159090.

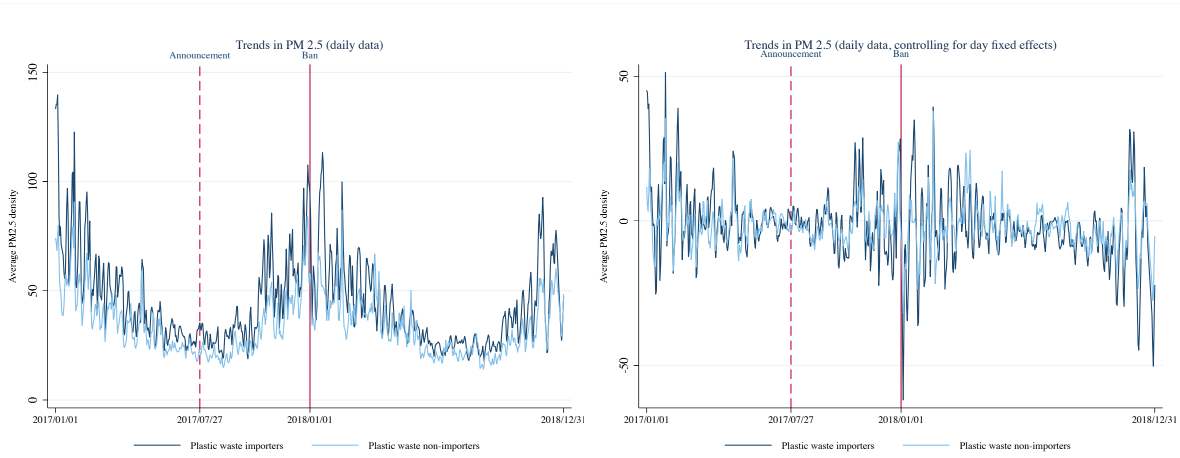


Figure A.5: $PM_{2.5}$ density in plastic waste importing cities and non-importing cities: Daily data

Notes: Figures show the average daily $PM_{2.5}$ density for plastic waste importing cities and non-importing cities over the period 2017-2018. The left figure shows the raw data and the right figures shows the de-trended data controlling for day of the year fixed effects. Plastic waste importing cities are those that imported any plastic waste during 2000 to 2011. The vertical lines mark policy changes: announcement of the import ban to the WTO in July 2017 (red dashed line), and the beginning of the ban (red line) in January 2018.

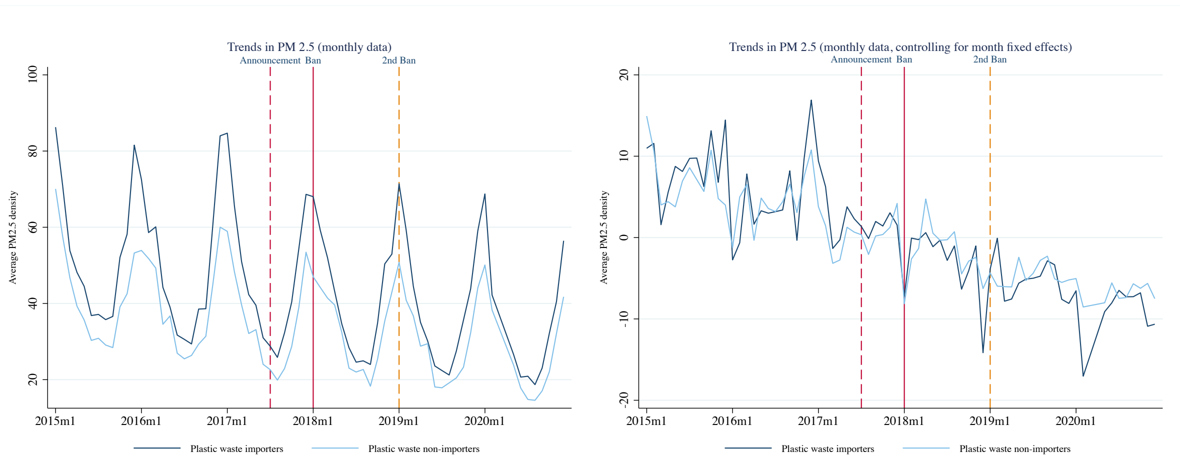


Figure A.6: $PM_{2.5}$ density in plastic waste importing and non-importing cities: Monthly data

Notes: Figures show the average monthly $PM_{2.5}$ density for plastic waste importing cities and non-importing cities over the period 2015-2020. The left figure shows the raw data and the right figures shows the de-trended data controlling for month fixed effects. Plastic waste importing cities are those that imported any plastic waste during 2000 to 2011. The vertical lines mark policy changes: announcement of the import ban to the WTO in July 2017 (red dashed line), the beginning of the ban (red line) in January 2018 and the second ban (orange dashed line) on December 31, 2018.

Table A.1: Summary statistics of key variables for the sample 2000-2011

	Mean	SD	Min.	Max.
Plastic waste imports (asinh)	3.38	4.18	0.00	14.31
Other waste imports (asinh)	5.03	4.89	0.00	16.09
Other imports (asinh)	11.64	3.57	0.00	20.16
Average $PM_{2.5}$ (SEDAC)	31.58	16.86	1.03	90.86
Maximum $PM_{2.5}$ (SEDAC)	45.80	18.25	2.70	113.20
Minimum $PM_{2.5}$ (SEDAC)	23.99	15.38	0.00	82.30
Average $PM_{2.5}$ (ACAG)	43.40	15.50	2.51	100.22
Population (ln)	5.70	0.81	2.04	8.11
Employment (ln)	5.06	0.88	-1.86	7.45
GDP per capita (ln)	9.46	0.84	7.06	12.03
Primary sector output share (%)	19.95	10.24	0.05	65.28
Secondary sector output share (%)	57.19	39.15	7.17	606.31
Average temperature (K)	12.38	5.85	-8.17	26.28
Precipitation rate (mm/hr)	2.52	0.47	0.96	4.06
Average humidity (kg/kg)	35.76	4.75	15.33	55.00
Wind speed west to east (m/s)	-3.10	4.97	-17.75	14.53
Wind speed south to north (m/s)	1.06	1.38	-2.53	7.40
Output of waste processing sector (asinh)	2.49	4.78	0.00	15.35
No. of plastic waste processing plants (asinh)	1.47	1.21	0.00	5.70
SOE	0.03	0.20	0.00	3.47
Private	0.39	0.72	0.00	5.04
Individual business	1.20	1.15	0.00	5.35
No. of fires (asinh)	4.86	1.92	0.00	9.83

Notes: This table reports summary statistics of key variables for the sample 2000-2011. All variables are measured at the city level on a yearly basis. $N = 3,869$.

Table A.2: Summary statistics of key variables for the sample 2015-2020

	Mean	SD	Min.	Max.
Plastic waste import city	0.89	0.31	0.00	1.00
Plastic waste import city (Median length)	0.69	0.46	0.00	1.00
Plastic waste import city (Prob≥50%)	0.55	0.50	0.00	1.00
Plastic waste import city (in 2011)	0.71	0.45	0.00	1.00
$PM_{2.5}$	43.55	36.87	1.00	2211.65
PM_{10}	76.61	66.41	1.00	30008.17
Air quality index (AQI)	70.06	45.96	1.00	500.00
Ozone (O_3)	84.60	39.11	1.00	1200.00
Sulphur dioxide (SO_2)	17.34	21.06	1.00	1594.05
Nitrogen dioxide (NO_2)	30.35	18.62	1.00	462.88
Carbon monoxide (CO)	0.93	0.58	0.00	73.64
Average temperature (K)	13.35	10.99	-32.58	34.00
Precipitation rate (mm/hr)	2.76	6.68	0.00	175.47
Average humidity (kg/kg)	75.28	19.38	0.00	100.00
Wind speed west to east (m/s)	-0.28	2.61	-19.22	17.00
Wind speed south to north (m/s)	0.04	3.06	-18.32	14.87
No. of plastic waste processing plants (asinh)	2.35	1.25	0.00	5.63
Individual business	1.43	1.10	0.00	5.31
SOE	0.01	0.14	0.00	3.69
Private	1.73	1.32	0.00	5.51
No. of fires (asinh)	0.28	0.72	0.00	7.52

Notes: This table reports summary statistics of key variables for the sample $2015-2020$. Plastic waste import city indicates those that imported plastic waste in any year between 2000 and 2011. Plastic waste import city (median length) indicate cities that imported plastic waste for at least four years, the median time length across cities between 2000 and 2011. Plastic waste import city (Prob≥50%) indicate cities that imported plastic waste for at least six years. Plastic waste import city (in 2011) denotes those that imported plastic waste in 2011. $PM_{2.5}$, PM_{10}, AQI, O_3, SO_2, NO_2, and CO are measured at the monitoring station level on a daily basis between 2015 and 2020. Average temperature, precipitation rate, humidity, wind speed, and the number of fires are measured at the city level on a daily basis. The number of plastic waste processing plants (total and by ownership) is measured at the city level on a yearly basis. $N = 2,933,330$.

Table A.3: First-stage estimation results

Dep. variable:	Exp_WLD× Imp. Prob.	Exp_SEA× Imp. Prob.	Exp_WLD× Port Dist.	Exp_SEA× Port Dist.
Pwaste imports (asinh)	(1)	(2)	(3)	(4)
Instrumental variable	2.719***	1.689***	7.871***	2.328***
(shown in column header)	(0.149)	(0.093)	(1.390)	(0.253)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	3,872	3,872	3,872	3,872
R^2	0.056	0.061	0.035	0.061

Notes: This table reports the first-stage estimation results of 2SLS regressions in Table 1 and Table 3. The dependent variable is the value of plastic waste imports, transformed by *asinh*. The instrumental variable is shown in column headers. All regressions control for a full set of city-level control variables and weather conditions as in Table 1. Standard errors clustered at the city level are reported in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

Table A.4: Plastic waste production, number of fires, and $PM_{2.5}$: 2000-2011

Dep. variable: PM2.5 density	(1)	(2)	(3)	(4)	(5)	(6)
WP production (asinh)	0.039					
	(0.027)					
No. of PW plants (asinh)		-0.080				
		(0.113)				
No. of PW plants: SOE (asinh)			-0.482			
			(0.371)			
No. of PW plants: Private (asinh)				0.384***		
				(0.133)		
No. of PW plants: Individual (asinh)					-0.169	
					(0.117)	
No. of fires (asinh)						0.785***
						(0.135)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,583	3,869	3,869	3,869	3,869	3,869

Notes: This table reports OLS estimation results of $PM_{2.5}$ density on the output of the waste processing industry, the number of newly registered plastic waste processing plants (total and by ownership), and the number of fires, all transformed by the inverse hyperbolic sine. Estimation sample is at the city level for the years $2000-2011$. All specifications include a full set of city-level control variables, weather controls, city fixed effects and year fixed effects. City-level control variables and weather controls are the same as in Table 1. Standard errors clustered at the city level are reported in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

Table A.5: Plastic waste imports and air quality: Lagged effects

Dep. variable:	SEDAC PM2.5	ACAG PM2.5
PM2.5 density	(1)	(2)
Lagged pwaste imports (asinh)	1.173***	0.683***
	(0.175)	(0.179)
First-stage KP F-statistics	296.403	296.819
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Observations	3,551	3,553

Notes: This table reports 2SLS estimation results of Equation (1) using lagged plastic waste imports (in *asinh*) by one year. Columns (1) and (2) use the average $PM_{2.5}$ density calculated from the SEDAC data and the ACAG data as the dependent variable, respectively. The instrumental variable in both columns is world total plastic waste export supply multiplied by the average import propensity of each city defined as Equation (2). Both specifications include a full set of city-level control variables, weather controls, city fixed effects and year fixed effects. City-level control variables and weather controls are the same as in Table 1. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Plastic waste import ban and $PM_{2.5}$: City-level regression results

Dep. variable: PM2.5 density	(1)	(2)
Pwaste importer×Ban	-2.434**	-3.113***
	(0.962)	(0.956)
Weather controls	Yes	Yes
Date FE	Yes	Yes
City FE	Yes	No
City×Day of year FE	No	Yes
Observations	705,985	705,985
R^2	0.465	0.624

Notes: This table reports OLS estimation results of equation Equation (4) at the city level. The dependent variable is the average $PM_{2.5}$ density in a city for each date. All specifications include a full set of weather controls and date fixed effects. Column (1) includes city fixed effects and column (2) includes city times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Plastic waste import ban, number of plastic waste processing plants, and air quality

Dep. variable:	No. of new PW plants (asinh)				PM 2.5 density			
As in column title	(1) Total	(2) SOE	(3) Private	(4) Ind.	(5) Total	(6) SOE	(7) Private	(8) Ind.
Pwaste importer×Ban	0.273**	0.015	0.417***	0.139				
	(0.113)	(0.010)	(0.105)	(0.115)				
No. of PW plants (asinh)					-0.272	1.386	-0.295	-0.231
					(0.187)	(0.873)	(0.187)	(0.185)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,996	1,996	1,996	1,996	1,996	1,996	1,996	1,996
R^2	0.716	0.579	0.723	0.590	0.927	0.927	0.927	0.927

Notes: This table reports OLS estimation results using data at the city-year level between 2015 and 2020. Columns (1) − (4) correspond to the estimations that regress the number of newly registered plastic waste processing plants (total and by ownership, all in *asinh*) on plastic waste importers interacted with the post ban dummy. Plastic waste importers are cities that imported plastic waste between 2000 and 2011. Columns (5) − (8) correspond to the estimations that regress the average $PM_{2.5}$ density on the number of new plastic waste processing firms (total and by ownership, all in *asinh*). All specifications include a full set of weather control variables as in Table 5, year fixed effects and city fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.8: Plastic waste import ban, number of fires, and air quality

Dep. variable:	No. of fires (asinh)		PM 2.5 density
As in column title	(1)	(2)	(3)
Pwaste importer×Ban	-0.022		
	(0.013)		
Pwaste import probability×Ban		-0.028**	
		(0.013)	
No. of fires (asinh)			0.835***
			(0.195)
Weather controls	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
City×Day of year FE	Yes	Yes	Yes
Observations	705,962	705,962	705,962
R^2	0.379	0.379	0.624

Notes: This table reports OLS estimation results using data at the city-date level between 2015 and 2020. Column (1) corresponds to the estimation that regresses the number of fires, transformed by inverse hyperbolic sine, on plastic waste importers interacted with the post ban dummy. Plastic waste importers are cities that imported plastic waste between 2000 and 2011. In column (2), the plastic waste importer indicator is replaced with the probability of importing plastic waste, which is defined as the share of years of importing plastic waste between 2000 and 2011. Column (3) corresponds to the estimation that regresses the average $PM_{2.5}$ density on the number of fires (in *asinh*). All specifications include a full set of weather control variables as in Table 5, date fixed effects and city times day of the year fixed effects. Standard errors clustered at the city level are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.