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Maestría en Economía

The Impact of China's Import Growth on United States Air Quality

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"El impacto del crecimiento de las importaciones chinas en la calidad del aire en los Estados Unidos"

Resumen

Este artículo estima los efectos de la notable alza de las importaciones chinas sobre la calidad del aire en los Estados Unidos durante el período 1990-2007. Para este fin, se estima el impacto de una medida de exposición a las importaciones ajustada por contaminación (que considera el grado relativo de contaminación asociada a cada producto) sobre la calidad del aire en condados de Estados Unidos. Esta medida se instrumenta empleando los cambios en las importaciones chinas de países de altos ingresos. Empleando una metodología de mínimos cuadrados en dos etapas encontramos que un incremento de las importaciones chinas está asociado con mejores niveles de calidad de aire en los condados presentes en la muestra.

Palabras clave: Medio Ambiente, Medio Ambiente y Comercio, Contaminación del Aire, Comercio Internacional

"The impact of China's import growth on United States air quality"

Abstract

This paper estimates the effects of the staggering rise of Chinese imports on United States counties air quality during the 1990-2007 period. For this purpose, we estimate the impact of a pollution-adjusted import exposure measure -that takes into account the relative degree of pollution associated with each product- on U.S. counties air quality. We instrument this measure using changes in Chinese imports in other high-income countries. Employing a two-stage least squares methodology, we find that the increase in Chinese imports is associated with better air quality levels in the U.S. counties present in our sample.

Keywords: Environment, Environment and Trade, Air Pollution, International Trade

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The Impact of China's Import Growth on United States Air Quality

Sebastian Vargas Macedo

This paper estimates the effects of the staggering rise of Chinese imports on United States counties air quality during the 1990-2007 period. For this purpose, we estimate the impact of a pollution-adjusted import exposure measure -that takes into account the relative degree of pollution associated with each product- on U.S. counties air quality. We instrument this measure using changes in Chinese imports in other high-income countries. Employing a two-stage least squares methodology, we find that the increase in Chinese imports is associated with better air quality levels in the U.S. counties present in our sample.

I. Introduction

Air pollution in the United States has been declining in the last decades. Table 1 shows just how stark these environmental improvements have been. Between 1990 and 2007[1], emissions of key pollutants that contribute to air contamination have declined on average 39% as reported on Table 1. Similarly, air quality, understood as the concentration of air pollutants in the air, has been improving. Table 2 shows that there is a significant decrease in the concentration of five major air pollutants during the past two decades.

The literature suggests three possible explanations for the declining air pollution levels during the last decades (Shapiro and Walker, 2018). First, stronger environmental regulations. For example, federal and state agencies require some firms to install increasingly stringent pollution abatement technology (Henderson 1996, Chay and Greenstone 2005, Correia et al 2013, Shapiro and Walker 2018, Deschenes, Shapiro and Greenstone 2017). Second, a more efficient production technology measured by an increase in total factor productivity. If manufacturing firms can produce the same amount of output using less inputs, then there is a potential reduction in emissions per unit of output (Shapiro and Walker 2018, Levinson 2015, Levinson 2009). Third, the substantial increase in U.S. manufacturing imports. If the U.S. traded local production of pollutant goods (like steel or cement) for imports produced abroad, the pollution may have fallen due to the decrease of local production of such goods. In this paper, we will analyze the relevance of this last explanation, and investigate the possible effects of trade with the U.S. mayor trade partner, China.

There is an important body of work that investigates the relationship between international trade and pollution (see Copeland and Taylor 2004 for a review of the theoretical and empirical literature). In their seminal paper Antweiler, Copeland and Taylor 2001 set the theorical ground for the possible effects of trade on pollution emissions. Using cross-country data, they found that freer trade is beneficial to the environment. Results are later corroborated by McAusland and Millimet, 2013 and and Frankel and Rose, 2005. Other studies have discerned the effects on environment depending on the income level of the countries involved in trade. For example, Le,

[1] Throughout this paper we will use this period for all our analysis to be consistent with Autor, Dorn and Hanson. (2013) and their respective crosswalks and imputations methodologies availability for imports and manufacturing employment data. We believe this 17 year period is enough to encompass the fast rise of Chinese imports in the U.S., whose growth rates were especially high in the 90's and early 2000's.

Chang and Park, 2016 find that the impact of trade is benign on high-income countries but harmful on middle-and low- income countries. The majority of the literature focus on cross-country level analysis, however there are some recent papers focusing on country level analysis. Levinson (2015) in his review of international trade and environmental consequences argues for a green shift in U.S. manufacturing, he claims U.S. is increasingly producing domestically a higher proportion of goods whose manufacturing generates relatively less pollution, and a lower proportion of goods whose manufacturing generates relatively more pollution. According to Levinson, one possible explanation for this green shift in U.S. manufacturing is that U.S. is increasingly importing the goods that generate the most pollution. Given the rise in manufacturing imports from China, it is natural to ask if trade with China has enable the United States to enjoy a cleaner environment at home by importing goods whose manufacturing process creates pollution abroad.

This paper will seek to find whether there has been or not an effect of the rapid growth of Chinese imports during the decades of 1990 and 2000 on air pollution in the U.S. Despite the attention payed to the relation between trade and pollution, there is a lack of studies that investigate the effect of trade shocks on pollution in the U.S., specially pertaining a bilateral trade relation, and to our knowledge there is no paper that study the effect of Chinese imports on U.S. air pollution[2].

Why China? The role of China in U.S. international trade cannot be understated. Following its rapid economic growth and transition to a market-oriented economy during the decade of 1990 and its incorporation into the World Trade Organization in 2001, the amount of Chinese imports grew by more than 1000% in the U.S. during the period between 1990 and 2007 outpacing the growth of exports to China by more that 600%. Table ***3*** reports that no other source of imports grew more in the country and that the influx of Chinese imports was more significant for the U.S. than for other high-income countries. Column 3 indicates that the growth in imports from low-income countries during the 1990-2007 period was less than half than the growth in imports from China. Furthermore, Autor, Dorn and Hanson (ADH, 2013) find that the share of total U.S.

[2] There is a previous work on the Ocean-Atmospheric field (Lin et al 2014) which estimates that 36% of sulfur dioxide (SO_2), 27% of nitrogen oxides (NO_x), 22% of carbon monoxide (CO) and 17% of black carbon emissions in China were associated with production of goods for export. For each of these pollutants, approximately 21% of the export-related emissions were associated with China-to-U.S. exports. Using an input-output model they calculate that, had the U.S. produced all the goods imported from China in 2006, the SO_2 emissions would be higher by 1.7%, 1.3% for NO_x, 0.8% for black carbon and 1.1% for CO.

spending on Chinese goods rose from 0.6 percent in 1991 to 4.6 percent on 2007 and called this sudden surge in imports from China the "China shock"[3]. This shock can be treated as exogenous using an instrumental variable approach as in ADH (2013)[4] or using the permanent normal trade relationship (PNTR) index as in Pierce and Schott (2016).

This paper will contribute to the literature of trade and its effects on the environment by measuring the effect of an exogenous trade shock, the China Shock, on the U.S. air quality levels. To do this, we construct a measure of pollution-adjusted import exposure to China and estimate the impact of this import measure on the air quality of U.S. counties. For the construction of this pollution-adjusted import measure we follow recent literature on Chinese imports impact in the U.S. at the local level, mainly we weight the import measure used in ADH (2013) by the pollution intensity in each imported industry. To account for the possibility of endogeneity in our import exposure measure, we instrument U.S. Chinese imports with other high-income countries imports from China. We additionally control for environmental regulation in the counties, the evolution in the number of manufacturing establishments, and we test for the presence of heterogeneous effects of imports on pollution by county characteristics. Our results suggest that there is a significant impact of Chinese imports on our measures of air quality under all the tested specifications for the period 1990-2007. We also find that the environmental regulation has a positive effect on improving air quality in the U.S.

The rest of the paper proceeds as follows. Section II discusses the theoretical foundations of our analysis, Section III presents our pollution-adjusted import exposure indicator, discusses the data and key variable measurements and lays out our empirical methodology. Section III presents the main results and Section IV concludes.

[3] Previous studies have used this shock to study the effect of the China shock on different types of outcomes in the U.S. For example, Che, Lu, Pierce, Schott and Tao (2017) estimate the impact of Chinese imports on congressional election outcomes and Pierce and Schott (2018) estimate the impact on mortality.
[4] Our identification strategy is related to the ADH instrument.

Table 1. Total emissions of key pollutants in the United States

	Levels			Ten-year equivalent change		
	1990	2000	2007	1990-2000	2000-2007	1990-2007
Carbon monoxide	143,604.6	102,418.0	75,228.3	-28.7%	-26.5%	-47.6%
Nitrogen oxide	25,027.3	23,845.1	15,675.3	-4.7%	-34.3%	-37.4%
PM10	22,908.6	21,500.7	18,197.6	-6.1%	-15.4%	-20.6%
PM2.5	6,256.4	5,880.9	5,391.9	-6.0%	-8.3%	-13.8%
Sulfur dioxide	18,833.7	11,643.4	4,603.6	-38.2%	-60.5%	-75.6%

Notes: Data from EPA's Air Pollutant Emissions Trends Database. Numbers correspond to total national annual emissions. Data for carbon monoxide, sulfur dioxide and nitrogen oxide does not include wildfire events.

Table 2. United States Air Quality Trends: Descriptive statistics for key air pollutants concentrations

	Levels			Ten-year equivalent change		
	1990	2000	2007	1990-2000	2000-2007	1990-2007
Carbon monoxide (ppm)	5.77	3.45	1.88	-40.2%	-45.4%	-67.3%
Nitrogen dioxide (ppb)	76.36	59.80	48.51	-21.7%	-18.9%	-36.5%
PM10 (ug/m3)	84.78	65.56	62.54	-22.7%	-4.6%	-26.2%
Ozone (ppm)	0.088	0.082	0.079	-6.6%	-3.9%	-10.2%
Sulfur Dioxide (ppb)	128.22	81.31	65.25	-36.6%	-19.8%	-49.1%

Notes: Data obtained from EPA's Air Trends database. Numbers correspond to mean annual values averaged over several locations across the U.S. The AQI is an index for reporting daily air quality. It tells you how clean or polluted your air is, and what associated health effects might be a concern for the population. EPA calculates the AQI for five major air pollutants regulated by the Clean Air Act: ground-level ozone, particle pollution (also known as particulate matter PM10), carbon monoxide, sulfur dioxide, and nitrogen dioxide. Think of the AQI as a yardstick that runs from 0 to 500. The higher the AQI value, the greater the level of air pollution and the greater the health concern. For example, an AQI value of 50 represents good air quality with little potential to affect public health, while an AQI value over 300 represents hazardous air quality.
ppm: parts per million; ppb: parts per billion; ug/m3: micrograms per cubic meter.

Table 3. Value of trade with China for the U.S. and other selected high-income countries and value of imports from all other source countries 1991/1992-2007

	I. Trade with China (in billions 2007 US$)		II. Imports from other countries (in billions 2007 US$)		
	Imports from China	Exports to China	Imports from other low-income countries	Imports from México / CAFTA	Imports from rest of world
	(1)	(2)	(3)	(4)	(5)
United States					
1991/1992	26.3	10.3	7.7	38.5	322.4
2000	121.6	23.0	22.8	151.6	650.0
2007	330.0	57.4	45.4	183.0	763.1
Growth 1991-2007	1,156%	456%	491%	375%	137%
Eight other developed countries					
1991/1992	28.2	26.6	9.2	2.8	723.6
2000	94.3	68.2	13.7	5.3	822.6
2007	262.8	196.9	31.0	11.6	1329.8
Growth 1991-2007	832%	639%	236%	316%	84%

Notes: Table obtained from Autor & Dorn (2013). Trade data comes from UN Comtrade Database for years 1991 (1992 for exports to China),2000,2007. "Other developed countries" comprises Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

II. Theoretical Foundation

There are two main theoretical mechanism of how trade might affect the environment (for a review of these see Copeland and Taylor 2004). First, there is the pollution haven theory, which states that countries with relatively weak environmental policy will specialize in "dirty" goods production. Using a Ricardian framework (Pethig 1976, Chichilnisky 1994) this theory predicts that, if two countries differ only in their environmental policy, expressed through a "pollution tax", then the country with the highest pollution tax (meaning stronger environmental policy) will have a comparative disadvantage in pollutant industries, hence opting for importing these goods from countries with weaker environmental regulation. Second, there is the "factor endowment hypothesis" (Copeland and Taylor 2004), which states that standard forces such as factor endowments or technology determine the specialization on dirty or clean goods production, with environmental policy playing no role on it. In other words, countries underlying production capacities will be the main factor determining the impact of trade on environment. If a country is relatively abundant in factors that are used intensively in the production of clean industries, then this country will specially in these products, will import goods associated with polluting industries from other countries, and will see its pollutants emissions decline.

We observe that the particularities of the Chinese trade shock can be related to baseline conditions present in both theories. On one hand, Chinese environmental regulation and enforcement has been weaker than in the U.S. (Fazio and Strell 2012, Etsy and Porter 2002), hence according to the pollution haven theory, U.S. should specialize in cleaner goods. On the other hand, with an abundance of low-priced labor relative to the U.S. it is no surprise that China specializes in the production of labor-intensive goods while U.S. specialized in the production of goods that are human/physical-capital intensive. According to Cole, Elliot and Shimamoto (2004) low-skill labor-intensive goods tend to be relatively cleaner goods while dirty sectors are generally intensive in physical and/or human capital. Since the predictions of these two theories go against each other it remains an empirical question which of these two effects will dominate. Furthermore, is important to highlight that China, an economy built on low-wage manufacturing, is moving its way up the skill and wage ladder, progressing from cheap emerging market to rich developed nation, this gradual restructuring of China's industrial sector has moved it toward more capital-intensive industries, meaning that China production could be focusing on dirtier goods.

III. Methodology and Data

a. Calculating Pollution-Adjusted Import Exposure Measure

The main goal of this paper is to estimate the impact of Chinese imports on county's air pollution at an aggregate level, hence we will not be interested in estimating and quantifying the structural channels through which this relationship might exist. We chose to adopt a partial equilibrium reduced-form approach wherein we will be estimating the supply-side driven effects of Chinese imports on U.S. counties air quality.

In using a reduced-form approach to estimate the impacts on pollution we are following recent empirical literature that have analyzed the relationship between imports from China and different types of outcome variables at the regional level in the United States. For example, Pierce and Schott (2016) developed a measure of import exposure (the PNTR index) to estimate the impact of Chinese imports on manufacturer employment in the U.S. Following up this work, Che, Lu, Pierce, Schott and Tao (2017) used the PNTR index to estimate the impact of Chinese imports on U.S. Congressional elections at the county level. Likewise, Pierce and Schott (2018) employ the PNTR to estimate the impact of Chinese imports on mortality at the county level. Similarly, Autor, Dorn and Hanson (2013) developed an import exposure indicator to estimate the impact of Chinese imports on manufacturing employment and wages at the commuting-zone level in the U.S.

Our main variable of interest is the pollution-adjusted import exposure measure. This measure is based on a modification of the import exposure measure first developed by Autor, Dorn and Hanson (2013). They construct a local labor market exposure to import competition as the change in Chinese import exposure per worker in a region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{ct} = \frac{\sum_i \frac{L_{cit}}{L_{uit}} \Delta ImportsUSCh_{it}}{L_{ct}} \quad (1)$$

Where $\Delta ImportsUSCh_{it}$ is the observed change in U.S. imports from China in industry *i* between the start and end of the period, L_{cit} represents the employment in industry *i* for region *c* at the beginning of period *t*, L_{uit} is the employment in industry *i* at the national level at the beginning of period *t*, and L_{ct} is the total non-agricultural employment in region *c* at the beginning of period *t*. This variable apportions imports per manufacturing industry at the national level to each region based on its share of national industry employment. Since not every industry generates the same amount of pollution per unit of output, we slightly modify the ΔIPW_{ct} measure to consider the relative differences in pollution emissions of each industry. Hence, our key indicator will follow:

$$\Delta PPW_{ct} = \frac{\sum_i \frac{\boldsymbol{\rho}_i L_{cit}}{L_{uit}} \Delta ImportsUSCh_{it}}{L_{ct}} \quad (2)$$

We are modifying the ΔIPW_{ct} in two ways. First by using U.S. county employment data from the previous decade instead of commuting zone employment. We want to take advantage of the sometimes-limited pollution data, which most disaggregated version is at the county level. And second and most importantly, by multiplying the imports per county and industry $(\frac{L_{cit}}{L_{uit}} \Delta ImportsUSCh_{it})$ by the emissions intensity ρ_i. This coefficient gives us the amount of pollution per unit of output of industry *i*, which allows us to represent the relative degrees of pollution-generating capacity associated to each amount of imports per industry and county. Hence, while the Autor and Dorn ΔIPW_{ct} indicator is in terms of imports per worker, our ΔPPW_{ct} indicator is in pollution per worker units. This can be understood as a measure of pollution-adjusted Chinese import exposition for each county. It can also be understood as a measure of the pollution amount that could have been potentially avoided by replacing local manufacturing production for

Chinese imports during the period of analysis. The multiplication of pollution intensities and import levels has been used in previous literature simply to do a descriptive analysis of the polluting content of U.S. imports (Schatan 2003, Kahn 2003, Ederington et al 2004, Levinson 2010b) but no relationship or causality among imports and pollution has been study.

Variations in ΔPPW_{ct} across counties will come from differences in the mix of manufacturing industries production in each county (proxied by the share of employment at the beginning of the period), and from the different levels of pollution intensities associated to the relevant industries per county. Hence, two counties that share the same value of their respective ADH (2013) ΔIPW_{ct} indicator could have different values of our ΔPPW_{ct} measure if their relevant industries have different pollution profiles.

Our identifications strategy relies in the fact that our import exposure measure is plausibly exogenous to U.S. county levels of pollutions. However, there exist the possibility that our import exposure measure is correlated with an unobserved industry demand shock that could have affected the demand for imports as well as the pollution levels through effects on local production. If this were the case, our estimates would be endogenous and biased. Hence, to correctly identify the effect of import exposure we will employ an instrumental variables approach. We will closely follow the instrument chosen by Autor, Dorn and Hanson 2013. Therefore, we will exploit the fact that the rise in Chinese exports during the period of analysis stems from a Chinese supply shock that consisted of increased competitiveness of Chinese manufacturers, lowering of trade barriers and the incorporation of China into the World Trade Organization. Hence, we will use as instrument a modified import exposure measure in which we replace the change in U.S. imports from China with the change in imports from China for eight other high-income countries[5]:

$$\Delta PPW_{oct} = \frac{\sum_i \frac{\rho_i L_{cit-1}}{L_{uit-1}} \Delta ImportsOthCh_{it}}{L_{ct-1}}$$

Where $\Delta ImportsOthCh_{it}$ is the observed change in imports from China to a group of high-income countries for industry *i* during the period *t.* The use of Chinese imports to other countries looks to account for a common cause in imports surge: Chinese supply shocks (from the perspective of the importers), thus providing a correlation with our U.S. import exposure measure. Also, we expect that local demand shocks are not related to Chinese imports to other countries, thus providing the independence of the instrument from the unobserved components in our main equation. On the

[5] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland. (Autor et al 2013)

other hand, the use of information of employment form the previous decade[6] looks to avoid the possibility of adjustments in anticipation of Chinese imports (Autor et al 2013).

b. Alternate Explanations

Furthermore, since it is implied that the relationship between import competition and change in air pollution possibly occurs through changes in production/number of manufacturing plants per county, it is important to consider the possibility of a local trend in manufacturing production that did not respond to the increased import competition and that could explain the decline in U.S. pollution. For this reason, we will control for local manufacturing production proxied by the change in the number of manufacturing establishments in each county for each period. Additionally, we control for the change in the number of manufacturing establishments in the *previous* decade to account for the possibility of a pre-existing trend in manufacturing production in each county.

We will also follow the related literature[7] by taking into account the possible role of environmental regulation in the evolution of air pollution in the U.S. For this purpose, we will control for regulation using a dummy variable that indicates whether a county was in "non-attainment status" at any time during the period of evaluation. Non-attainment status occurs when harmful pollutant levels exceed the standard set by the Environmental Protection Agency (EPA)[8]. If a county reaches non-attainment status the corresponding State must submit an implementation plan to the EPA in order to meet federally mandated deadlines for compliance with the air quality standards. Hence, our control variable for environmental regulation will indicate if the county implemented active measures to reduce its air pollution levels.

Finally, we will evaluate the presence of heterogeneous effects. In particular, we are interested in testing the presence of additional impacts for counties that had, at the beginning of each decade a larger number of manufacturing establishments. For this purpose, we include a dummy equal to one for counties with more than 200 establishments in 1990 or 2000, and interact it with our import exposure measure.

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[6] i.e. for the period 1990-2000 we use 1980's employment levels, while for 2000-2007 we use 1990's employment information.

[7] See for example, Deschenes et al 2017, Shapiro and Walker 2018, Henderson 1996, Correia et al 2013.

[8] These limits are called National Ambient Air Quality Standards and are set by the EPA following the mandate of the Clean Air Act.

c. **Data and Measurements**

Data for air pollution at the county level comes from the EPA's Air Quality Index (AQI). This index is an indicator of overall air quality, which takes into account five types of air pollutants: Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Ozone (O_3), Sulfur Dioxide (SO_2) and Particulate Matter[9]. These pollutants are measured in different locations across several U.S. counties. The AQI is classified in six categories indicating increasing levels of health concern[10]. The AQI runs from 0 to 500. The higher the AQI value, the greater the level of air pollution and the greater the health concern. Table 4 presents the different categories for each AQI value, where a value 50 of below means a good level of air quality index little danger to public health, while an AQI value above 50 represents air quality that is considered unhealthy.

We take AQI data for year 1990, 2000 and 2007. We construct three measures of air pollution per county and year: (i) the percentage of days per year for which the air pollution was considered moderate, unhealthy, very unhealthy or hazardous (i.e. days for which the AQI was above 50)[11]; (ii) the median value of county's daily AQI per year and (iii) the 90th percentile of county's daily AQI per year. We were able to obtain AQI information for 1002 unique counties in the U.S, for which we have data for 750 counties for the period 1990-2000 and 950 counties for the period 2000-2007, thus the panel data is unbalanced.

Table 4. Air Quality Index categories

Air Quality Index Value	Levels
0 to 50	Good
51 to 100	Moderate
101 to 150	Unhealthy for sensitive groups
151 to 200	Unhealthy
201 to 300	Very Unhealthy
301 to 500	Hazardous

Note: Classification by Environmental Protection Agency (EPA).

Data for Chinese imports in U.S. and other high-income countries comes from the UN Comrade Database, at the six-digit harmonized system product level. We obtained data for the years 1991,

[9] Smaller that 10 micrometers and 2.5 micrometers (PM10 and PM2.5, respectively).
[10] Environmental Protection Agency. https://www.airnow.gov/aqi/aqi-basics
[11] The percentage is based on the total days per year for which there was a AQI measure.

2000, 2007, all in 2007 US$ values[12]. This data was converted to four-digit Standard Industrial Classification (SIC) Codes and slightly aggregated following ADH (2013) criteria in order to guarantee a match for each HS trade code and avoid immunity to trade[13] by construction for some industries. For our analysis we use import data for the SIC codes corresponding to manufacturing. Data on local manufacturing employment and number of manufacturing establishments at the county level was obtained from the County Business Patterns (CBP) databases for years 1980, 1990, 2000, and 2007 available at the U.S. Census Bureau. This database provides annual county data by industry of employment (measured in number of workers), number of establishments, and annual payroll. Given that the number of employees by county and industry is sometimes reported as an interval, and that some establishments are not identified at the four digits SIC codes, we use the Autor and Dorn (2013) methodology for imputing values for employment an industry for these observations.

Information for pollution intensities was obtained from the Industrial Pollution Projection System (IPPS) database developed by the World Bank. This dataset provides estimates of emissions of different types of pollutants for each SIC code based on facility-level data from the U.S. Census of Manufactures, Aerometric Information Retrieval System, National Pollution Discharge Elimination System and Toxics Release Inventory. The intensities are reported in tons of pollutant per value of output (measured in thousands of 1987 U.S. dollars, which we later adjust to 2007 U.S. dollars to make it consistent with the import data). To construct the industry emission intensities ρ_i (used in equation (2)) we aggregate -add up- by SIC code the pollution intensities of the five type of air pollutant present in the AQI calculation[14]. The resulting coefficient is our ρ_i that will multiply the imports per county and industry in equation 2.

We obtained data for non-attainment status of U.S. counties from EPA's Green Book Data Dictionary. We used yearly information from 1992(first year available) to 2007 to construct dummy variables for each county and time period. The dummy takes value equal to one if the

[12] We use 1991 instead of 1990 since that is the first year for which trade data across many hight income countries, which are used for our instrument. This is because there existed a lag in countries adopting the HS classification.

[13] Which means that without the aggregation, the original HS-SIC crosswalk used by ADH would leave some SIC codes without a corresponding six-digit HS code and hence those industries would have zero imports in our database. The aggregation leaves us with trade data for every SIC code.

[14] These are: Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2) and Particulate Matter smaller than 10 micrometers (PM10).

county achieved non-attainment status for any of the criteria pollutants in any year of the period 1990-2000 or 2000-2007.

Table 5. Summary statistics for key variables at the county level

	Ten-year equivalent change		
	1990-2000	2000-2007	1990-2007
Change in days with AQI at or above moderate levels	5.23 (20.43)	-0.42 (14.11)	2.08 (17.41)
Change in median yearly AQI	1.65 (15.82)	0.35 (10.06)	0.93 (12.93)
Change in 90^{th} percentile yearly AQI	-2.57 (28.43)	-2.89 (19.53)	-2.75 (23.86)
Change in import exposure per worker (in tons of pollutant)	5.40 (11.05)	13.44 (25.21)	9.90 (20.61)
Instrument variable: Change in import exposure per worker (in tons of pollutant) (Other countries)	5.41 (13.38)	23.40 (57.68)	15.46 (44.91)
Change in number of manufacturing establishments	-28.22 (182.06)	-24.93 (122.28)	-26.38 (151.52)
Counties with 200 or more manufacturing establishments	0.38 (0.48)	0.32 (0.47)	0.35 (0.48)
Non-attainment status dummy	0.52 (0.50)	0.44 (0.50)	0.48 (0.50)
Observations	750	950	1700

Notes: First row for each variable report means while standard deviations are reported on parentheses.

d. Empirical Specification

We examine the link between Chinese import exposure and county pollution using a generalized OLS stacked first difference specification that examines whether county pollution declines are higher in counties with high pollution-adjusted imports per worker ($\Delta \mathrm{PPW}_{ct}$ is high) relative to counties with low pollution-adjusted imports per worker. We stack first differences of two periods, 1990 to 2000 and 2000 to 2007 and estimate the following equation:

$$\Delta Pollution_{ct} = \beta_1 \Delta \mathrm{PPW}_{ct} + \mathbf{X}'_{ct}\beta_2 + \delta_t + \varepsilon_{ct}$$

Where t=1990-2000, 2000-2007, c is county and i is the manufacturing SIC code. Where the dependent variable, $\Delta Pollution_{ct}$ is the change in one of our three measures of air pollution for the two-time spans[15]. The first term on the right-hand side, $\Delta \mathrm{PPW}_{ct}$,corresponds to the change in pollution-adjusted imports per worker for the two-time spans. The second term on the right-hand side, $\mathbf{X'}_{ct}$, is a vector of control variables; these include a dummy variable that takes value equal to one if county c achieved non-attainment status at any point during each decade, this term accounts for the role of environmental regulations in the period of analysis. We also control for the change in the number of manufacturing establishments in county c for each decade and the change in the number of manufacturing establishments in the *previous* decade. We include the change in manufacturing establishments as a proxy for manufacturing production at the county level to account for the possibility of omitted variable bias, since there could exist a trend in local production related to the change of imports that has an impact on air pollution through the emissions resulting from the manufacturing processes. We also control for past trends in manufacturing establishment evolution (measured as the change in the number of manufacturing establishments of the previous decade) in order to account for the possibility of pollution being determined in part by an ongoing trend in manufacturing production in the counties. Finally, we include a time dummy δ_t equal to zero for 1990-2000 and one for 2000-2007.

This equation is equivalent to a three-period fixed effect model with the assumption that the error term is not serially correlated. Since we use standard errors clustered at the county level, the estimates should be robust to the error structure.[16]

However, as previously stated, to account for the possibility of endogeneity in our import exposure measure due to unobservable industry demand shocks, we will instrument with the variable ΔPPW_{oct} as previously described. Therefore, we will implement a two stage least squares (2SLS) methodology by which we will estimate, in the first stage, an pollution-adjusted import exposure measure free of potential correlation with unobserved industry demand shock; and in the second stage, we will estimate the relationship between air pollution and our endogeneity-corrected an pollution-adjusted import exposure measure.

[15] i.e. $\Delta Pollution_{c1990} = Pollution_{c2000} - Pollution_{c1990}$ and $\Delta Pollution_{c2000} = Pollutin_{c2007} - Pollution_{c2000}$

[16] We follow Autor, Dorn and Hanson 2013 for this specification and robustness strategy. See also Wooldridge 2002.

IV. Results

a. Main Results

Table 6 first presents the OLS estimates for multiple regressions grouped by our three measures of air pollution. Columns (1), (3) and (5) provide the estimates for a simple regression on ΔPPW_{ct} with no additional control variables, while columns (2), (4) and (6) provide estimates of our main equation with all the controls. We observe that all the estimates for our pollution-adjusted import exposure per worker measure are negative and significant for the 1990-2007 period, indicating that an increase in our Chinese imports measure coincides with a lower air pollution per county. Furthermore, the coefficients are very robust to the inclusion of controls.

Table 7 presents our main results from our 2SLS estimation. At the bottom of the table we present the first stage estimates while at the top of the table we present the second stage estimates for each specification. The first stage results show a positive and significant estimate in all scenarios, indicating that the instrument used is a good fit for our pollution-adjusted import exposure measure. We tested for under-identification and weak identification and rejected both hypotheses. For the second stage, we observe that our estimates are all negative and significant, except for the specification with no controls for the 90th percentile of AQI measure (column 5). Comparing these results with those from Table 6 we observe a slight bias correction thanks to the use of our instrument. Additionally, we see in Table 8 that the coefficients for the specifications with and without controls are very similar, with the coefficients of the full control models, columns 2, 4 and 6 being slightly larger. This suggests that the corrected endogeneity bias is not that large.

The estimated effects are also economically significant. A one-standard deviation of our import exposure measure PPW_{ct}[17] (equal to 21 tons/per worker – see Table 5) leads to an average reduction of 1.1 in the share of unhealthy AQI days per year ($21 \times -0.0524 = 1.1$). Similarly, column 4 shows us that one standard deviation increase in out import measure, PPW_{ct}, leads to an average reduction of 1 point in the median AQI for a county, and an average reduction of 1.4 points in the county's AQI's 90th percentile.

[17] Which could also be interpreted as tons of "outshored" air pollutants per worker.

We can compare these effects with the effect of the environmental regulation variable. Counties that have non-attainment status (dummy variable that proxies the county implementation of active measures to reduce its air pollution levels) have on average 1.4 points lower share of unhealthy AQI than counties without non-attainment status. In addition, we observe that counties with non-attainment status experience a reduction in the median AQI of 1.8 points and a reduction in the 90th percentile of AQI of 1.7 points. These results are in line with the related literature which finds significant effects of environmental regulation on air pollution levels. Economically speaking, although the magnitude in terms of absolute value of the Chinese import exposure measure on county pollution is small, in relative terms it appears that the China shock has comparable effects on county pollution as the environmental regulation variable.

Additionally, we find a small but a positive and significant relationship between the number of manufacturing establishments and our air pollution measures. First, we see that a decrease of one standard deviation (equal to 151 establishments – see Table 5) in the number of establishments implies a reduction of 0.52 percentage points in the share of moderate to hazardous days. Additionally, we see that one standard deviation decrease in the same variable leads to an average decrease of 1 point in the median AQI and 2.1 points in the 90th percentile AQI. Interestingly, we find no significant effect on the previous decade change in the number of establishments (except for the specification with the 90th percentile change in AQI where there is a small positive relation), which indicates that pre-existing trends at the beginning of the sample period did not affect the change in air quality for the counties in our sample.

b. Heterogenous Effects

Holmes and Stevens (2013) show that increased import competition from China can have heterogeneous effects among plants within an industry, with the biggest negative effect (exit of plants) observed at large plants producing standardized goods, while small plants producing specialty goods are less affected. We extrapolate this conclusion to the county level and study the possible existence of heterogenous effects of imports from China on pollution among counties with different size. Where county size is measured by the number of manufacturing establishments per county. We construct a dummy variable that takes a value of one if in the beginning of each period the county had 200 or more manufacturing establishments (large county) and takes a value of zero otherwise. We interact this dummy with our import exposure measure $\Delta\ \mathrm{PPW}_{ct}$.

Table 8 shows the results of the estimation with the interaction term. We only find evidence of a significant effect for our 90th percentile measure of AQI. Interestingly, the estimated coefficient is positive, which suggests that the Chinese imports effects on pollution are smaller if the county has a large number of manufacturing firms.

V. Conclusions

Pollutant emissions in the U.S. have been declining during the period of 1990-2007, averaging an approximate 40% decrease for some key pollutants. The literature has focused on three explanations for the decrease in manufacturing industry-related emissions: environmental regulation, improvements in productivity and the increase in manufacturing imports. Regarding the last explanation, the literature has found many times a benign effect of international trade on the environment, employing, most of the time, large cross-country data for their estimates. However, there is a lack of evidence of the impact that a dramatic change in bilateral trade relations could have had on the environment in one of the countries involved. We have shown that the staggering 1,156% increase in Chinese imports to the U.S. during the period 1990-2007 is a good example of such shock. As a matter of fact, this dramatic increase in imports have been the subject of recent empirical studies that look for impacts on this shock on a diverse range of outcomes in the U.S., such as manufacturing employment, Congressional elections and mortality rates.

In this paper, we have estimated the impact of the rise of Chinese imports on the air quality levels in the U.S. counties during the 1990-2007 period. For this we have relied on a pollution-adjusted import exposure measure at the county level that aims to measure the degree of exposure to Chinese imports that each county's local manufacturing industry had, taking into consideration different degrees of pollution associated with each industry. Given the fact that unobserved shocks could have affected both the import demand and local production (and, hence, pollution emissions), we instrument the growth of imports from China with Chinese import growth in other high-income countries.

Our analysis finds a negative relationship between Chinese imports and air pollution in U.S. counties. Using a 2SLS approach we show that counties with higher import exposure experience larger declines in air pollution. The magnitude of the effect is comparable to the effect of environmental regulations (or having non-attainment status) on counties' air pollution. These results are robust to inclusion of variables proxying for alternate explanations as previous trends (decline) in manufacturing production and the increase in environmental regulations. We find no significant evidence of heterogeneous effects by county size, measure by the number of manufacturing establishments per county. Our results, mirror findings in the literature made in cross-country studies with respect to the positive effects of international trade on the environment[18] Additionally, they contribute to the growing evidence of the impact of China's import growth on the United States during the last decade on a wide array of outcomes.

[18] Antweiler et. al., 2001, McAusland and Millimet ,2013, Frankel and Rose, 2005 and Le et al, 2016 to name a few.

Table 6. Imports from China and change in air pollution, 1990-2007: OLS Estimates

	(1) Change in % of unhealthy AQI days	(2) Change in % of unhealthy AQI days	(3) Change in median AQI	(4) Change in median AQI	(5) Change in 90th percentile AQI	(6) Change in 90th percentile AQI
Δ Pollution-adjusted import exposure per worker	-0.0499***	-0.0530***	-0.0422***	-0.0452***	-0.0540**	-0.0587**
	(0.017)	(0.017)	(0.013)	(0.013)	(0.026)	(0.026)
Δ(Number of manufacturing establishments)		0.00432*		0.00695***		0.0140***
		(0.002)		(0.002)		(0.004)
Δ(Number of manufacturing establishments)(t-1)		0.00200		-0.00229		-0.00827**
		(0.002)		(0.002)		(0.004)
Non-attainment status		-1.360*		-1.793***		-1.667
		(0.753)		(0.591)		(1.107)
Observations	1700	1693	1700	1693	1700	1693
R^2	0.029	0.035	0.007	0.018	0.002	0.009

Notes: The OLS estimation for the variables in first differences is equivalent to a three period fixed effect models with serially uncorrelated errors. Data for 1002 counties. Some counties lack pollution information for a period, hence the N is lower than 2002. Robust standard error in parenthesis are clustered on county. One standard deviation of Δ Pollution-adjusted import exposure per worker is equal to 21.

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 7. Imports from China and change in air pollution, 1990-2007: 2SLS Estimates

	(1) Change in % of unhealthy AQI days	(2) Change in % of unhealthy AQI days	(3) Change in median AQI	(4) Change in median AQI	(5) Change in 90th percentile AQI	(6) Change in 90th percentile AQI
Δ Pollution-adjusted import exposure per worker	-0.0494**	-0.0524**	-0.0417**	-0.0446**	-0.0612	-0.0656*
	(0.024)	(0.024)	(0.021)	(0.021)	(0.037)	(0.038)
Δ(Number of manufacturing establishments)		0.00432*		0.00695***		0.0141***
		(0.002)		(0.002)		(0.004)
Non-attainment status		-1.360*		-1.793***		-1.670
		(0.751)		(0.590)		(1.104)
Δ(Number of manufacturing establishments) (t-1)		0.00200		-0.00229		-0.00829**
		(0.002)		(0.002)		(0.004)
R^2	0.029	0.035	0.007	0.018	0.002	0.009
	2SLS First Stage Estimates – Dependent variable: Δ Pollution-adjusted import exposure per worker					
Δ (Import exposure -Other Countries)/Worker	0.3362***	0.3357***	0.3362***	0.3357***	0.3362***	0.3357***
	(.026)	(0.026)	(.026)	(0.026)	(.026)	(0.026)
R^2	0.55	0.55	0.55	0.55	0.55	0.55
Observations	1700	1693	1700	1693	1700	1693

Notes: The estimated equation in first differences is equivalent to a three-period fixed effect model with serially uncorrelated errors. Data for 1002 counties, with information for 750 counties for period 1990-2000 and 950 for 2000-2007. All regressions include a constant and a dummy for the 2000-2007 period. First stage estimates also include the control variables present in the corresponding column. Robust standard errors in parenthesis are clustered on county. One standard deviation of Δ(Import exposure)/Worker is equal to 21.
*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 8. Imports from China and change in air pollution, 1990-2007: OLS and 2SLS Estimates with interaction terms

	(1) Change in % of unhealthy AQI days	(2) Change in % of unhealthy AQI days	(3) Change in median AQI	(4) Change in median AQI	(5) Change in 90th percentile AQI	(6) Change in 90th percentile AQI
Δ Pollution-adjusted import exposure per worker	-0.0560***	-0.0548**	-0.0483***	-0.0475**	-0.0780***	-0.0816*
	(0.019)	(0.026)	(0.015)	(0.023)	(0.029)	(0.042)
Δ(Number of manufacturing establishments)	0.00412	0.00412	0.00643***	0.00644***	0.0134***	0.0134***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
Non-attainment status	-1.352*	-1.352*	-1.687***	-1.687***	-1.832	-1.831
	(0.800)	(0.799)	(0.635)	(0.634)	(1.180)	(1.177)
Δ(Number of manufacturing establishments) (t-1)	0.00211	0.00211	-0.00198	-0.00198	-0.00795*	-0.00794*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
(Δ Pollution-adjusted import exposure per worker)*(More than 200 manufacturing establishments at t)	0.0219	0.0208	0.0165	0.0157	0.154***	0.157**
	(0.046)	(0.048)	(0.030)	(0.034)	(0.058)	(0.064)
More than 200 manufacturing establishments at t	-0.245	-0.231	-0.534	-0.525	-0.953	-0.993
	(0.898)	(0.912)	(0.660)	(0.680)	(1.284)	(1.321)
R^2	0.035	0.035	0.018	0.018	0.011	0.011
	2SLS First Stage Estimates – Dependent variable: Δ Pollution-adjusted import exposure per worker					
Δ (Traded Pollution with China-Other Countries)/Worker		0.3144***		0.3144***		0.3144***
		(0.026)		(0.026)		(0.026)
R^2		0.59		0.59		0.59
Observations	1693	1693	1693	1693	1693	1693

Notes: The estimated equation in first differences is equivalent to a three-period fixed effect model with serially uncorrelated errors. Data for 1002 counties, with information for 750 counties for period 1990-2000 and 950 for 2000-2007. All regressions include a constant and a dummy for the 2000-2007 period. First stage estimates also include the control variables present in the corresponding column. Robust standard errors in parenthesis are clustered on county. One standard deviation of Δ(Import exposure)/Worker is equal to 21. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

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