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Trade Openness, Pollution, and Growth: Evidence from China, 1998-2008

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Trade Openness, Pollution, and Growth: Evidence from China, 1998-2008

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Abstract

The debate over trade liberalization mainly comes from doubts about its consequences on economic growth and the environment. This study directly investigates such question in the context of China and assesses several candidate explanations for the underlying channels using detailed county-level data from 1998 to 2008. We instrument county-level trade shocks by assembling the change in product-level tariffs and the county's industrial structure. It is found that tariff reduction on inputs promotes economic growth and decreases the pollution levels, while tariff reduction on outputs harms the environment. We highlight the mechanisms of the impacts on emission, involving (i) scale, composition, and technique effects, and (ii) composition of tariff reductions. The findings reveal a weak pattern of the Pollution Haven Hypothesis. This work further evaluates the gains on economy and environment from the tariff reform in China.

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The competition arising [from WTO membership] will also promote a more rapid and more healthy development of China's national economy.

— Premier Zhu Rongji (Press release, Washington, DC, April 1999)

China's entry into the WTO will instill new vitality into the economic growth of China as well as other countries and regions in Asia and beyond. The Chinese people will benefit from it, and so will the people of other countries in Asia and the world.

— President Jiang Zemin (Speech at Fortune Global Forum, Hong Kong, Sept. 2001)

[F]or the last ten years environmentalists and the trade policy community have engaged in a heated debate over the environmental consequences of liberalized trade.

—Copeland and Taylor, 2004

1 Introduction

This work aims at addressing two increasingly heated questions regarding trade liberalization: *What is the effect of trade openness on regional environment and economy?* and *What is the underlying mechanism?* To do so, we estimate the impacts of import competition induced by trade openness on environmental and economic performances from about 3000 counties in the context of China. We then feature three possible underlying mechanisms to shed light on how import competition affects the regional environment. With a focus on China, this work points toward gains from trade openness on both economic growth and environmental quality.

The empirical setting applied in this study follows the course of China's Opening-Up and WTO accession. During this process, the Chinese government concurrently reduced tariffs on imported goods as a unilateral basis. Especially during the period from 1998 to 2008, China underwent its major tariff declines with its rapid growth on both economy and imports, as well as great environmental damages.¹ Our identification, which is similar to several regional studies on trade shocks, relies on the compelling setting that regions

¹The trade liberalization process in China started much later, which was different from many other developing counties that experienced their trade liberalization episodes throughout the 1980s and 1990s, such as Brazil, Mexico, and India.

within a country exogenously differ in their exposure to import competition (tariff reductions) as a result of variations of different regional characteristics.² Taking advantage of this identification, we construct China's county-level import tariff on input and output based on product-level tariff and county-level industrial structure. The isolated two trade shocks derive two primary intuitions behind: (i) import tariff cuts on inputs (hereafter 'input tariff') could provide cheaper intermediates to lower regional production cost; (ii) import tariff cuts on outputs (hereafter 'output tariff') could lower the final good price therefore make the domestic market more competitive.

We link the constructed county-level tariffs to comprehensive data covering information on socioeconomic characteristics and pollutant emissions for about 3000 counties in China over the period from 1998 to 2008. Our benchmark results indicate that reduction on input tariff rate leads to faster economic growth and better environmental quality, while output tariff reduction shows a negative impact on the environment. In particular, 1% input tariff reduction can contribute 0.9~1.5% economic growth, implying a great power of trade openness on explaining China's remarkable development. On the other hand, our results report that a more competitive domestic market caused by tariff reductions on output does not significantly harm China's economy. In our analysis on the dynamic pattern of trade openness, it indicates an adjustment process in the context of China: output tariff reductions had significant negative impacts on the domestic economy during the first three years since China joined WTO in 2001, but this negative impacts disappeared after 2004. There were no statistically significant impacts of input tariff reductions during the first three years, but such impacts became significant since 2004.

The empirical findings on how trade openness affects environmental quality provide a more comprehensive framework for understanding the impacts of trade shocks. This is an important test as a considerable amount of opponents to trade liberalization argues that developing countries/regions bear more pollution and become the 'pollution havens' with the process of trade liberalization. The pieces of evidence provided by this study suggest more informative understandings: on the one hand, impacts of trade liberalization

²See, for example, [Edmonds, Pavcnik and Topalova \(2010\)](#); [Topalova \(2010\)](#); [Kovak \(2013\)](#); [Autor, Dorn and Hanson \(2013\)](#); [Hakobyan and McLaren \(2016\)](#); [Dix-Carneiro and Kovak \(2017\)](#).

on environment quality go in two pathways, the input tariff reductions can improve the environment while output tariff reductions do the opposite. On the other hand, trade openness not only affects the total amount of pollution emissions but also affects cleaner technology upgrading as well as the reallocation of the scale of emissions.

We examine a variety of alternative mechanisms that might account for the liberalization's effects on regional environmental performance. First, the evidence sheds light on how input and output tariffs affect emissions through scale, composition, and technique effects: cuts in input tariff could affect local emission by increasing the scale of economy and reducing the emission intensity; cuts in output tariff only increase the total amount of emission by increasing the emission intensity. Second, we link the pollutant to its related tariff reductions to examine how different components of tariff reductions affect pollutant emissions, and our findings support the interpretations driven by comparative advantage. Intuitively, as cuts in input tariff provide more access to cheaper intermediates, local polluting industries could be mostly affected and they can have an opportunity to change their inputs structures to make less emission. Cuts in output tariff make the domestic market more competitive, the local polluted industries might choose to pollute more to enhance their competitiveness. Third, we find a weak Pollution Haven Effect by integrating the trade shocks, economy, and the environment in the context of China.

This study makes several contributions. Our first contribution is to provide the first empirical evidence of how trade liberalization affects regional pollutant emissions. By using the detailed county-level information on pollutant emissions, this work captures the most accurate and important outcomes from the environmental behavior responses. Directly utilizing the information on emission has several advantages on measuring the environmental performance: (i) pollutants in the water, air, or soil can diffuse across boundaries, therefore the spill-over effects could cause bias in estimators; (ii) ambient pollutants are also the products of chemical reactions, which are always associated with local environmental conditions. Further controls on meteorological factors (e.g. wind, temperature, precipitation) are sometimes needed; (ii) different pollutant emissions also allow us to investigate more detailed heterogeneity across different sectors.

Second, this study first separately estimates the impacts of input and output tariffs

on environmental performance, as many studies originally did for firm-level response.³ As the import tariff could have separate impacts through its shocks on both inputs and outputs, respectively influencing the intermediates and final goods market, the isolated tariff allows us to explore more detailed information about how import competition affect the regional environment. Our findings confirm that import tariff could affect the environment through the above mentioned two paths with different directions.

Finally, we contribute on examining the Pollution Haven Hypothesis (PHH).⁴ The PHH implies that both lower production cost and the more competitive market could spur regions to specialize in production in which they have a comparative advantage. As a result, polluted industries could be shifted from richer to poorer regions. Most studies tested this hypothesis from only one-side framework, which only replies on the one setting referring to either lower production cost or a more competitive market. This study takes advantage of both types of tariffs and can provide two pieces information on both sides. Our findings suggest a weak channel through the Pollution Haven Hypothesis that trade liberalization does not significantly drive the transfer of polluted industries across counties in China. In particular, we only find that a more competitive domestic market induced by output tariff reduction could differentiate the pollutants across counties, whose impacts are also very small. Our findings also suggest that lower production cost does not shift pollutants into China, as polluting industries could also have more access to clean inputs.

Our work relates to several strands of literature. It first stands in a broader literature analyzing the trade shocks and response from regions and firms. First, recent studies have become increasingly interested in analyzing the relationship between the trade shocks and firm-level behaviors on markups, productivity, competition, quality, sales, value added, employment as well as environmental performance.⁵ On the one hand, firm-level studies suggest that lowering tariff on inputs (imports of intermediate goods)

³See, for example, [Amiti and Konings \(2007\)](#); [Goldberg et al. \(2010\)](#); [Amiti and Davis \(2011\)](#); [Topalova and Khandelwal \(2011\)](#); [Bustos \(2011\)](#); [Amiti and Khandelwal \(2013\)](#); [Yu \(2015\)](#); [Fan, Li and Yeaple \(2015\)](#); [Halpern, Koren and Szeidl \(2015\)](#); [Brandt et al. \(2017\)](#); [Cherniwchan \(2017\)](#); [Fan, Li and Yeaple \(2018\)](#); [Bastos, Silva and Verhoogen \(2018\)](#); [Gutiérrez and Teshima \(2018\)](#).

⁴See, for example, [He, Xie and Zhang \(2018\)](#).

⁵See footnote 3 for the summary of the related literature.

directly reduces marginal costs, promotes firms' productivity and outputs, and finally decreases the markups (Tybout and Westbrook, 1995; Amiti and Konings, 2007; Goldberg et al., 2010; Bustos, 2011; Topalova and Khandelwal, 2011; Yu, 2015; Halpern, Koren and Szeidl, 2015; Brandt et al., 2017). In particular, initial lower-productivity firms are more likely to upgrade the quality of final goods and imported intermediates and experience more increase in their workforce and productivity (Fan, Li and Yeaple, 2018).

On the other hand, firm-level studies also indicate that lowering tariffs on outputs intensifies competition in the domestic market. A more competitive market can (1) induce firms with market power to lower their markups, (2) promote productivity or efficiency, and in return reduce the markups and marginal cost for production (Levinsohn, 1993; Gutiérrez and Teshima, 2018). In terms of environmental quality, the study of Gutiérrez and Teshima (2018) on firms in Mexico reports that both pollution emissions and direct investment in environmental protection fall with the reduction in output tariff.

Second, beginning with the seminal work of Frankel and Romer (1995), there appear more studies integrating trade shocks, economic growth, and environment at the regional or global level. Most studies utilize the trading volume or intensity as identification to explore their results, while only a few recent papers make use of tariff changes as the exogenous trade shock.⁶ The findings on the regional or global scale are similar in many ways compared to firm-level studies. For example, lowering tariff on inputs can raise the domestic outputs (industry output and GDP) due to the lower production cost (Keller and Yeaple, 2009; Goldberg et al., 2010; Schularick and Solomou, 2011; Connolly and Yi, 2015; Sequeira, 2016; Dix-Carneiro and Kovak, 2017). In terms of regional environmental quality, many studies reveal a positive relationship using trade intensity or trade quantities as a proxy for openness (Antweiler, Copeland and Taylor, 2001; Harbaugh, Levinson and Wilson, 2002; Frankel and Rose, 2005; Chintrakarn and Millimet, 2006; Cherniwchan, 2017).⁷ Only in recent years, a few papers use the tariff reductions as identification and their results suggest that domestic competitive market induced by output tariff reduction

⁶In trade economics, besides tariff reductions, many other instruments are applied for the proxy of trade cost reduction or trade openness index, for example, Yanikkaya (2003); Galor and Mountford (2008); Feyrer (2009a,b); Pascali (2017).

⁷See Copeland and Taylor (2004) for a review of the literature.

helps to reduce the total amount of emissions ([Gutiérrez and Teshima, 2018](#)). Additionally, some also argue that trade openness may benefit the domestic environment in relative polluted regions by a spread of the public awareness of environmental protection ([Grossman and Krueger, 1991](#)).

This study also links to literature focused on gains from trade, which allows us to understand the *cost* and *benefit* of the trade liberalization.⁸ Therefore, if trade openness is estimated to have adverse effects on the environment and growth, environmental policy and trade policy can be regarded as each other's substitute to further adjust the clock of globalization. In fact, increasing number of literature argue that import competition induced by trade openness can create unemployment and welfare loss, reduce the wage growth, cause violent crimes, and even increase the suicide rate.⁹ Our findings quantitatively provide insights on China's gains from trade due to the tariff reforms, including the gains on economic growth, pollutant emissions as well as improvement of air quality. We also provide evidence on a dynamic adjustment process to show how China's economy gradually adapted itself to benefit from input tariff reductions and avoid the competitions from cuts in output tariff.

Additionally, our work speaks to literature focusing on the relationship between the economy and environment.¹⁰ Different from existing studies testing a two-dimension relationship such as Environmental Kuznets Curve (EKC), we provide insights on a three-dimension framework integrating the trade shocks to the environment-economy relationship. We show that, as tariff reductions simultaneously cause changes in both the environment and economy, these trade-offs could differ and depend on the regions' characteristics. In the context of China during our research period from 1998 to 2008, we document a weak positive relationship between the economic growth and environment environmental damages in initial poorer regions.

⁸See, for example, [Arkolakis, Costinot and Rodriguez-Clare \(2012\)](#); [Connolly and Yi \(2015\)](#); [Sequeira \(2016\)](#); [Costinot and Rodriguez-Clare \(2018\)](#).

⁹See, for example, [Autor, Dorn and Hanson \(2013\)](#); [Caliendo and Parro \(2015\)](#); [Pierce and Schott \(2016\)](#); [Autor, Dorn and Hanson \(2016\)](#); [Pierce and Schott \(2017\)](#); [Asquith et al. \(2017\)](#); [Dix-Carneiro and Kovak \(2017\)](#); [Majlesi and Narciso \(2018\)](#); [Dell, Feigenberg and Teshima \(2018\)](#); [Hakobyan and McLaren \(2018\)](#).

¹⁰See, for example, [Grossman and Krueger \(1991\)](#); [Copeland and Taylor \(1994\)](#); [Arrow et al. \(1995\)](#); [Jaffe et al. \(1995\)](#); [Antweiler, Copeland and Taylor \(2001\)](#); [Copeland and Taylor \(2004\)](#); [Faber \(2014\)](#); [He, Xie and Zhang \(2018\)](#).

This study is most closely related to the work of [Gutiérrez and Teshima \(2018\)](#) in Mexico at the zip-code level during 2000 to 2003. In a similar specification as ours, their paper reveals that the reduction in output tariffs leads to less energy use, lower pollution level, and less environmental investment. This paper improves this line of literature in several ways. Firstly, both the environment and economy are investigated in the same framework to present more styled facts on the different consequences of trade shocks. More importantly, our measurement of outcomes directly captures the emissions, imply several advantages as mentioned above. Secondly, the data used in this study are a larger panel from 1998 to 2008 with about 3000 counties, especially covering the most important decades when China decided to join the WTO. Thirdly, this work includes both output tariff and input tariff as independent variables, where the latter is not controlled in [Gutiérrez and Teshima \(2018\)](#). In addition to the advantages mentioned above, more importantly, our findings indicate that input tariff shows statistically significant impacts on economy and environment in many ways. The underlying channels of input tariff perform more variously compared to output tariff, too. Fourthly, this study directly investigates the polluting emissions at the county level, while this important measurement is not available in the [Gutiérrez and Teshima \(2018\)](#)'s dataset. Finally, this study explores the channels in more detail to explain the changes in environmental quality.

Two other studies have also looked at the impact of trade on the environment but with different identification strategy. [Bombardini and Li \(2016\)](#) estimated how trade shocks affect China's city-level pollution and infant mortality. They apply export tariff reduction controlled by that of the rest of the world as identification. This study differs because it focuses on trade shock induced by import tariff reductions and directly captures the industrial emissions as outcomes. [Cherniwchan \(2017\)](#) studied the environmental consequence of trade barriers reduction in the context of U.S focused on the firm level. However, we are also different in use of our identification: in [Cherniwchan \(2017\)](#)'s paper, the trade shock is measured by trade volumes rather the tariff reduction.

In addition to being an important area of research, this issue is of considerable interests to politicians and the public. The last few years have seen heated debates on the North American Free Trade Agreement (NAFTA), the Trans-Pacific Partnership (TPP), as

well as the General Agreement on Tariffs and Trade (GATT), which act as the foundation of the World Trade Organization (WTO). Currently, the political controversies over trade liberalization have not only emerged in economic development, employment, and wage growth but also extended to its impacts on the environment, health, education, public security, even civilization, and democracy.¹¹ In particular, this policy ramification becomes more fierce in recent years when Donald Trump pulled the U.S. out of the TPP deal and launched the trade war with China, whose impressive growth was often attributed to the accession to trade openness.

This paper proceeds as follows. Section 2 reviews the relevant history and institutional context of China's trade liberalization and lays out the measurement of trade openness at county level. Section 3 describes the econometric strategy. Section 4 introduces the data and provides descriptive statistics. Section 5 reports the benchmark results and evaluates the gains from trade in the context of China. Section 6 discusses a series of potential mechanisms to interpret the results. The paper ends with concluding remarks in Section 7.

¹¹One notable example from China is that the China's central government decided to stop the imports on nonindustrial plastic waste due to the concerns on environment and public health: <https://www.scmp.com/news/china/policies-politics/article/2103587/china-bans-imports-garbage-overseas>.

2 Quantification of County Level Trade Openness

2.1 Trade Liberalization in China

As one of the most important parts of its 'Reform and Opening' economic policy, China ended nearly 30 years of extremely high trade barriers and embarked on a radical path of trade liberalization since the early 1980s. In practice, it introduced a series of policies to allow the entrance of foreign direct investment (FDI), to relax the restrictions on importation, to encourage the imports on much-needed capitals, and to license and import more new technologies. Even before its accession to the WTO in 2001, China has reduced its domestic import tariffs from 43.2% in 1992 (unweighted average at the 8-digit Harmonized System (HS) level) to 15.3% in 2001 ([Branstetter and Lardy, 2008](#)).

China became a WTO member on December 11, 2001, when it gave a commitment to reduce all bound tariffs to about 10% on average over a five-year period. The unilateral trade liberalization involved large declines in average trade barriers and non-tariff barriers and featured substantial variation in tariff cuts across products.

The tariff reductions offered by the trade liberalization typically spurred the processing trade and a more competitive domestic market in China. In the context of processing trade, which is encouraged by import tariff reductions on inputs, the domestic firm initially imports all or part of the raw materials or intermediate inputs from abroad and re-exports the final value-added goods after local processing or assembly ([Feenstra and Hanson, 2005](#)). The processing trade only shared less than 10% of China's total imports in the early 1980s. However, with its dramatically increasing, more than 50% of total imports were accounted by processing trade in 1990s ([Yu, 2015](#)).

On the other hand, China's domestic market became more competitive due to the increasing and more accessible imports from the rest of the world. As shown in [Figure 1](#), taking 1994 as the base year, the importation on the trade volumes of both intermediates and final goods have increased 135.5% and 69.1% from 1994 to 2001, respectively. Owing largely to China's accession to the WTO in 2001, the situation has changed markedly. The trade volumes of intermediates and final goods in 2008 increased respectively more than 14 and 4 times than 1994, with an inflection point around 2001 when China joined the

WTO.

>>> **Figure 1** Here <<<

Figure 1 also displays additional notable divergences between the growing importation of intermediates and final goods during my study period 1998-2008. Following the reduction in trade barriers, overall imports increased, particularly on the intermediate inputs. The imports on intermediates grew faster than final goods in general, and this difference became bigger since China's accession to WTO in 2001. The proportion of imports on intermediates increased from 18.8% in 2001 to 32.0% in 2008. The increasing trend on the share of imported intermediates indicates a progressive importance of intermediates in imports.¹²

2.2 Tariff-based County-level Trade Liberalization Index

This study relates the changes in the import tariff on intermediates (input) and final goods (output) from 1998 to 2008 to changes in China's county-level outcomes, as the import tariff provides the most accurate and detailed information on trade openness.¹³ The counties differ in their exposures to tariff changes as a result of regional variation of different industrial structure. This subsection presents how to construct a county-level trade openness index to represent the county-level exposure to tariff changes.

The basic idea to construct this trade openness index is to map the product-level import tariff into the county level by utilizing each county's industrial structure data. This process can be divided into three main steps. The first is to transfer the product-level import tariff to the industrial-level specific output tariff, using the concordance between the classifications of product and Industry. The second is to generate the tariff on input from the output tariff based on China's 2002 Input-Output (IO) table. The last step is to construct the county-level tariff by merging the county-level industrial share with the

¹²**Figure A.1** provides the information on the shares of imports on intermediates and final good. Although the growth rate of intermediates was faster, the imports on final goods still dominated the total trade volumes during 1994 to 2008.

¹³Another important form of measurement of trade openness is nontariff barriers (NTBs). However, NTBs are generally very difficult to quantify ([Amiti and Konings, 2007](#)). This study is, unfortunately, unable to find any further information on NTBs, thus the analysis here focuses on the effects of the tariff reform.

industrial-level specific tariff. As a result, two kinds of tariff-based county-level trade liberalization indexes can be constructed. One refers to the tariff rates on the inputs (intermediates) to the country's production, and the other kind is the rates on the outputs (final goods). Both indexes represent import competition from the rest of the world because of the trade openness.

The first and second steps of this work follow the approach proposed by [Brandt et al. \(2017\)](#) in the context of China.¹⁴ The product-level import tariff rates are obtained at the 8-digit level of the Harmonized System (HS) product classification from the World Integrated Trade Solution (WITS) database of the World Bank. By using the concordance between the 8-digit level HS and the 4-digit level China's Industrial Classification (CIC) system, the product-level tariff rates are mapped into the industrial level (424 manufacturing industries) as the tariff rates on outputs. As a result, the 4-digit industrial level output tariffs are constructed by taking a simple average of the HS 8-digit code within each 4-digit CIC code.¹⁵

In the second step, the industrial-level input tariffs are constructed as a weighted average of output tariffs, using the industrial input shares from China's 2002 Input-Output (IO) table. Thus, if industry s uses 70 percent inputs from cement manufacturing and 30 percent from engine manufacturing, the input tariff for that industry equals to 70 percent of the cement manufacturing tariff plus 30 percent of the engine manufacturing tariff, which is constructed in the first step. As a result, the industrial-level input and output tariffs are both constructed at the 4-digit level of CIC system. To deal with changes in CIC codes in 2003, some industries are merged to obtain a consistent classification over the entire sample period based on the concordance built by [Brandt et al. \(2017\)](#).

The last step is to construct the county-level tariffs, which are calculated by [Eq.1](#). The county-level industrial share and industrial-level tariffs are combined to obtain the

¹⁴This approach is similar to several previous firm-level studies. For example, [Amiti and Konings \(2007\)](#); [Topalova and Khandelwal \(2011\)](#); [Fan, Li and Yeaple \(2015, 2018\)](#); [Gutiérrez and Teshima \(2018\)](#).

¹⁵As documented in [Brandt et al. \(2017\)](#), taking the unweighted average can avoid any bias caused by the low trade volumes in heavily protected product lines. Simple average and weighted average are both applied in literature. For example, simple average has been used in [Amiti and Konings \(2007\)](#); [Brandt et al. \(2017\)](#), and weighted average in [Topalova and Khandelwal \(2011\)](#); [Gutiérrez and Teshima \(2018\)](#).

weighted average county-level tariffs as a proxy to the trade openness.¹⁶ For example, if 70 percent of a county's industrial output is accounted by cement manufacturing with the engine manufacturing sharing the other 30 percent, I give a 70 percent weight to the cement manufacturing tariff and a 30 percent weight to the engine manufacturing tariff. In Eq.1, $CT_{i,t}$ represents the county-level weighted average tariff for county i in year t ; $S_{i,s,t}$ refers to the industrial output of industrial s for county i in year t ; $S_{i,t}$ is the total industrial output for county i in year t ; $T_{s,t}$ indexes the tariff for industry s in year t . In practice, the county-level input tariff and output tariff are calculated separately using Eq.1 as $CIT_{i,t}$ and $COT_{i,t}$.

$$CT_{i,t} = \frac{\sum_s S_{i,s,t} T_{s,t}}{\sum S_{i,t}} \quad (1)$$

In Eq.1, the industrial-level tariff on inputs and outputs ($T_{s,t}$) is derived from the second step. The county-level annual industrial output ($S_{i,s,t}$) for the period 1998-2007 is obtained through the annual survey conducted by the National Bureau of Statistics (NBS). The survey covers all industrial firms that are either state-owned or non-state firms with the annual sales larger than 5 million CNY. It contains firm-level production and accounting information such as employment, capital stock, gross output, value added, and firm identification (e.g., company name, telephone number, zip code, contact person). In particular, the survey documents each firm's county-level administrative address and its 4-digit level CIC code, which allows each firm to be matched to the corresponding county and each industrial sector matched with corresponding the industrial-specific tariffs.¹⁷

Figure 2 shows the evolution of import tariffs on industrial-level and county-level inputs and outputs during the sample period.¹⁸ A number of patterns stand out for the re-

¹⁶Previous literature have documented several methods to capture the regional exposure to trade liberalization induced by import competition, such as regional imports (Autor, Dorn and Hanson, 2013; Costa, Garred and Pessoa, 2016) and industrial labor share (Topalova, 2010; Edmonds, Pavcnik and Topalova, 2010; Kovak, 2013; Bombardini and Li, 2016; Hakobyan and McLaren, 2016; Dix-Carneiro and Kovak, 2017; Gutiérrez and Teshima, 2018). Most methods make us of the pattern of regional comparative advantage to construct this regional index.

¹⁷More details on the data are given in Brandt, Biesebroeck and Zhang (2012, 2014); Yu (2015); Brandt et al. (2017); Fan, Li and Yeaple (2018).

¹⁸The evolution of industrial-level import tariffs is shown in Figure A.2.

ductions in county-level tariff. First, the county-level tariffs underwent similar reduction patterns, with an inflection point in 2001. Second, the constructed county-level tariff on outputs is slightly higher than the industrial level, implying the regions on average contain more industries with relatively high input tariff. Third, the reduction of both input and output tariffs spurts, with large and widespread reductions occurring in 2001, while these reductions were more gradual in other years. Fifth, output tariffs were on average substantially higher than input tariffs, reflecting the different treatment of final goods from raw materials, intermediates inputs, and capital imports. Finally, the reduction narrowed the gap between the median output and input tariffs, where this gap decreased from 7.0% in 2008 to less than 4.0% in 2007.

>>> **Figure 2** Here <<<

The average evolution hides important variation both across counties and within counties over time, thus it is interesting to estimate the effects of the trade liberalization on the county-level performance. The shaded area in **Figure 2 (b)** denotes the interquartile range for county-level output tariffs, and the dashed lines the corresponding interquartile range for county-level input tariffs. Counties initially differed tremendously in the protection they received. The narrowing trend of the two bands over time highlights the dropped important tariff compression: for county-level output tariffs, the interquartile range from 14-23% in 1998 to 7-11% in 2007.

Figure 3 maps the spatial variation in the county-level tariff reductions. Counties facing larger cuts in the tariff are displayed as bluer, while counties facing smaller reductions are shown as redder. As the panel information is not balanced and contains missing values, the counties have no data is presented as transparent. **Figure 3 (a)** indicates that most counties underwent the cuts in input tariffs ranging from 0 to 10 percent, and only a few counties experienced more than 20 percent input tariff reductions.¹⁹ As for the output tariff reductions, the majority of the counties faced 10 to 20 percent tariff reductions, while more than 40 percent output tariff cuts happened in a very few counties (**Figure 3 (b)**). However, both maps do not imply any spatial difference across China. The coastal coun-

¹⁹**Figure A.3** displays the spatial patterns of county-level tariff on inputs and outputs in 1998 and 2007.

ties do not observably experience larger tariff reductions compared to the inland areas. In particular, it is notable that the tariff increased in a few counties, and the maps display that all these counties are located in the inland areas. The unobvious spatial pattern also suggests an insignificant selection effect that probably no region has not enough power to affect the changes in tariffs.

>>> **Figure 3** Here <<<

2.3 Endogeneity Analysis

In order to consistently identify the impacts of regional tariff reductions, an important question is whether the trade reform process is endogenous, which would lead to biased estimates. First, certain industries or counties may have more political power to lobby the central government for protection ([Grossman and Helpman, 1994](#)), which causes the reverse causality. At industrial level tariff reduction, it suggests that the central government may selectively lower the tariffs in the industries where the domestic firms have higher productivity. However, [Brandt et al. \(2017\)](#) ruled out this concern by examining that the initial productivity is uncorrelated with the changes in tariffs. At regional level tariff reductions, however, there are about 3000 counties in China and each of them does not possibly have enough political or economic power to affect the central government's tariff reduction policy.

To investigate more formally whether the variations in trade liberalization is related to past county-level performance, I regress changes in tariffs between 1998 and 2007 on initial social and economic characteristics, using the similar method as [Topalova and Khandelwal \(2011\)](#); [Dix-Carneiro and Kovak \(2017\)](#) and [Brandt et al. \(2017\)](#). The economic characteristics are represented by the night light intensity, the number of lights and per capita lights from the United States Air Force Defense Meteorological Satellite Program (DMSP), which will be further discussed in [Section 4](#). For social characteristics, the county-level population and area were examined in 1998, which is the initial year in the sample period. The baseline results are presented in [Table 1](#). Columns (1) to (6) show that the subsequent

tariff cuts tend to be uncorrelated with economic characteristics. Although the number of lights indicates a positive relationship with a 10% significance level, the signs differ from other two economic measurements. Columns (7) and (8) show that the tariff changes are still uncorrelated when including other social conditions. Additionally, the insignificant spatial pattern of tariff reductions in China ([Figure 3](#)) also support this finding that no region has the evident tariff reductions. As suggested by [Mobarak and Purbasari \(2005\)](#), it is generally difficult for governments in developing countries to provide this kind of favors on protection because they could be under the close scrutiny of international organizations, such as the International Monetary Fund (IMF). To conclude, no relationship was found between county-level characteristics and cuts in tariffs, implying this endogeneity concern can be neglected in the context of China.

>>> [Table 1](#) Here <<<

The second concern refers to omitted variables. To reduce this potential bias, this study includes various fixed effects. On the one hand, the county fixed effects can account for any time-invariant county-specific characteristics and policies. The province and city fixed effects are also included to control any province/city-specific characteristics and policies that might affect outcomes for all counties within the same province/city. So if any regional factors are time-invariant, this is already accounted for. On the other hand, for time-variant common shocks to all counties across years such as national policy, the year fixed effects are controlled to reduced this concern.

However, it may still remain some time-variant omitted factors could simultaneously influence the county-level outcomes and tariffs. This omitted factors would require that (i) drives the changes in outcomes within a county and (2) is correlated county-level tariff reductions but (3) is not captured by the included fixed effects. For example, the export tariff faced by China is also changing over time. This potential bias is also unlikely to be a serious problem because the export tariff imposed on China were largely outside of China's control, which can be viewed as unilateral trade liberalization. In the context of WTO accession, it does not require corresponding changes in its trading partners' import barriers ([Ju, Shi and Wei, 2012](#)). Besides, China's major trading partners had already

granted Most Favored Nation (WTO) treatment to China long before China joined WTO ([Fan, Li and Yeaple, 2015](#)). Generally, such a feature is unlikely to exist. To further control this concern, this study follows [Brandt et al. \(2017\)](#)'s approach to use the maximum allowable tariff under the WTO agreement as the instrument from 2001 onward, which is pre-determined in 1999 when China has not joined the WTO.

3 Empirical Framework

This paper's empirical analysis follows the literature on the regional effects of trade by comparing the evolution of outcomes on environmental performance and economy in counties facing large tariff declines to those in counties facing smaller tariff declines. The baseline model follows the two-step approach in [Pavcnik \(2002\)](#), where the county-level performance measures $y_{i,t}$ are constructed on socioeconomic and environmental outcomes. Then we regress them on indicators of trade openness, county-level tariffs on input and output. [Eq.2](#) indicates the baseline econometric model.

$$y_{i,t} = \alpha + \beta_0 CIT_{i,t-1} + \beta_1 COT_{i,t-1} + \rho_i + u_t + \varepsilon_{i,t} \quad (2)$$

$$\widehat{CIT}_{i,t-1} = \alpha + \beta \text{MaximumInputTariff}_{i,t-1} + \rho_i + u_t + \varepsilon_{i,t} \quad (3)$$

$$\widehat{COT}_{i,t-1} = \alpha + \beta \text{MaximumOutputTariff}_{i,t-1} + \rho_i + u_t + \varepsilon_{i,t} \quad (4)$$

where we include county-fixed effects ρ_i and year-fixed effects u_t in the baseline regression. $CIT_{i,t}$ and $COT_{i,t}$ refers to the county-level input and output tariffs, respectively. $\varepsilon_{i,t}$ is the error term independent from ρ_i and u_t . The instrument for $CIT_{i,t}$ and $COT_{i,t}$ from 2001 onward is the maximum allowable tariff under the WTO agreement, and these county-level maximum tariff is also constructed using the same approach as the actual ones.

In the regression model, the county fixed effects control for the county's characteristics which do not change over time, and the year fixed effects to control for the common shock to all counties across years. The coefficients of $CIT_{i,t}$ and $COT_{i,t}$ represent the impacts of two types of tariffs. Standard errors are primarily clustered at the county level, where the independent variable's variations come from. For a robust check, this paper also follows [Cameron, Gelbach and Miller \(2011\)](#)'s multiple ways to cluster the standard errors in other different levels.

4 Data

In this work, a database is compiled which consists of the most detailed and comprehensive data available on county-level socioeconomic and environmental status from 1998 to 2008. This section describes the data with its sources and presents summary statistics on the general trends in the key variables and their spatial distributions.

4.1 Emission

The county-level emission data from 2000 to 2008 are collected from China's Environmental Survey and Reporting (ESR) database. The database is yearly updated by the Ministry of Environmental Protection (MEP). It includes all important emission sources, consisting of industrial firms, hospitals, waste treatment plants, and residential pollutant units. This database accounts for approximately 85% of the major pollutants at the county level (i.e., wastewater, chemical oxygen demand (COD), ammonia nitrogen ($\text{NH}_3\text{-N}$), sulfur dioxide (SO_2), industrial smoke and dust, as well as solid waste). In this study, the sulfur dioxide and COD are selected as the main outcomes on emissions as they are the most representative and important emitted pollutants.

The emission information is first self-reported annually or seasonally by the corresponding emitters to the county-level Environmental Protection Bureaus (EPB). Then the EPBs will conduct monitoring activities and unannounced field inspections to verify the authenticity and accuracy of the information. For emitters with complex administrative structures (such as joint enterprises, electricity bureaus, and management bureaus in the oil fields and mines), their branch plants are considered as the basic units for reporting the emission information. These data probably can be regarded as the most reliable and comprehensive data for the study of county-level pollutant emissions in China. Recently it has been used by [Lin \(2013\)](#); [Cai, Chen and Gong \(2016\)](#); [Wu et al. \(2017\)](#) and [He, Xie and Zhang \(2018\)](#).

4.2 Demographic and Socioeconomic Data

The demographic and socioeconomic data were constructed from two main sources. The first is the county-level socioeconomic data, obtained from various China Statistical Yearbook (County Level). This database indicates the county-level GDP, population, and per capita GDP, which are part of the outcomes of interests. However, there are at least three drawbacks for directly applying the GDP as the outcome. First, many counties have missing values on GDP. These missing values are not random because most of them come from the county-level urban districts. Second, the county-level Consumer Price Index (CPI) is unavailable to deflate the nominal GDP, which may create bias in the estimation. Third, the quality of the county-level GDP is not reliable enough due to several concerns on measurement errors and data manipulation.²⁰

To overcome these limitations, the luminosity at night was selected to be a proxy for the local economic activity. The use of lights data follows the assumption that there exists a strong within-country correlation between light density at night and GDP levels and growth rates. Several studies have assessed the viability of such assumption (Elvidge et al., 1997; Chen and Nordhaus, 2011; Henderson, Storeygard and Weil, 2012). Faced with a lack of reliable socioeconomic data, especially in developing countries, numerous authors have applied this proxy at low levels of spatial disaggregation.²¹

The luminosity data is primarily collected from the Defense Meteorological Satellite Program's Operational Linescan System which reports images of the earth at night captured from 20: 30 to 22: 00 local time. The satellite detects lights from human settlements, fires, gas flares, the lightning, and the aurora. A measure is a six-bit number (ranging from 0 to 63) calculated for every 30-second area (approximately 1 km²). The resulting annual composite images of time-stable lights are created by overlaying all images captured during a calendar year. Images, where lights are shrouded by clouds or overpowered by the aurora or solar glare the (near the poles), were dropped, and the ephemeral lights like

²⁰There are many reported manipulations on China's regional GDP. Here are some news for example: <https://www.wsj.com/articles/real-news-on-fake-data-in-China-1515573859> and <https://www.scmp.com/news/china/economy/article/2145790/first-it-faked-its-data-now-inner-mongolias-late-releasing>.

²¹See, for example, Michalopoulos and Papaioannou (2013, 2014); Hodler and Raschky (2014); Alesina, Michalopoulos and Papaioannou (2016); Berazneva and Byker (2017); Corral and Schling (2017); Lee (2018).

fires and lightning were removed.²²

This study uses the annual luminosity data at a resolution of 1 km².²³ We map the nighttime light to each county by a grid-area-based weighted average method (described in detail in [Appendix A.1](#)). [Figure 4](#) displays the nighttime lights in China in 1998 and 2008. The data on night light density was obtained by uniting the gridded nighttime light data and the county map. By multiplying the each county's light density and area, the information on the number of lights is also obtained. For robust concern, a cross-validation is conducted to investigate the relationship between the luminosity and economic performance at the county level. Details about cross-validation can be found in [Appendix A.2](#).

>>> [Figure 4](#) Here <<<

The luminosity data helps address several concerns. First, all the counties are covered by the satellites, thus there is no missing value issue. Each county's number of lights and light density data can be proxies for GDP and per capita GDP, respectively. Second, nominal GDP is required to be deflated to real GDP, while the nighttime lights across years are more comparable. Third, the nightlight data is more reliable than the statistical data from yearbooks. In particular, this data is open to the public since 2011, implying that the nightlight information is unknown to the county-level government during my sampled period 1998 to 2008. Thus the county-level government tends to have extremely low motivation to deliberately control their local lights ([Chen and Nordhaus, 2011](#); [Henderson, Storeygard and Weil, 2012](#); [Donaldson and Storeygard, 2016](#)).

4.3 Descriptive Statistics

[Table 2](#) provides summary statistics at county level. As panel A indicates, the tariff on inputs (about 8.6%) is lower than the output (about 14.3%) by comparing the average tariff rates. In particular, the 0 value of minimum suggests that some counties face a none tariff on inputs and outputs. The basic statistical pattern on max. tariffs and real tariffs

²²More information about the data can be found from https://ngdc.noaa.gov/eog/dmsp_docs.html.

²³The data can be downloaded from <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>.

look very similar. Panel B reports the pollutant emissions from the ESR. Primarily this study examines the various patterns of the consequences of trade shocks on these different pollutants. Panel C summarizes the county-level socioeconomic characteristics. The data on population and GDP are from various China's county-level yearbooks. The nighttime light density indicates the light intensity in a county, ranging from 0 to 63. The light density data acts as a good proxy for per capita GDP (income) in the empirical framework. To get the data on number of lights, this work simply multiplies each county's area with its nighttime light density.

>>> **Table 2** Here <<<

5 Results

This section is divided into three segments with benchmark results. First, this work measures the impacts of trade openness on county-level socioeconomic performance. Second, the consequences of pollutant emissions are estimated. The above two benchmark results are estimated from Eq.2 using corresponding county-level outcomes. Finally, following the findings from the benchmark results, the county-level gains from trade in China are illustrated by each county's different exposure to tariff reductions.

5.1 Effects on County-level Socioeconomic Performance

Table 3 shows the estimation of effects of tariff reductions on the county-level socioeconomic performance, where the county-level nighttime light performance was used as a proxy for local socioeconomic characteristics, including GDP and per capita GDP (Chen and Nordhaus, 2011; Henderson, Storeygard and Weil, 2012). Both independent variables (input tariff and output tariff) are lagged for one year. Panel A presents the OLS estimation results. In Panel B, the maximum allowable tariff rates under the WTO agreement are applied as instrumental variables from 2001 onward. Local economy showed statistically significant and positive correlation with the input tariff reduction, while all the correlation coefficients between local economy and output tariff reduction are very small (about 0.1%) and statistically insignificant.

>>> Table 3 Here <<<

Columns (1) and (2) of Table 3 report the impacts of tariffs on the nighttime light density. The positive correlation between the light density and per capita GDP is also validated in Appendix A.2. The negative and statistically significant estimates for input tariff imply that reductions on input tariffs increase the county-level light density. A one percentage point decrease in input tariff would lead to an average of 1.0~1.4% increase in the light density. Columns (3) and (4) use the sum of lights as the dependent variable, which can be viewed as a proxy for GDP. Similarly, the results suggest that a one percent decrease in input tariff rate can increase 1.1~1.5% nighttime light.

The robustness of these results is tested in three ways. (1) Instrumental variables. (2) County and year fixed effects are included for each estimator. In even columns, the province-year fixed effect is also included to control any within province policies that might commonly affect the outcomes for all counties in the same province. (3) For alternative measurement on the per capita GDP, per capita lights were computed as the dependent variable into the regression in columns (5) and (6). The per capita lights is defined as each county's number of lights over its population. Consistently, these coefficients range from $-0.9 \sim -1.2\%$ and remain statistically significant, which show similar magnitude with the results in columns (1) and (2). All three ways mentioned above support the robust impact of trade openness on the local economy.

To estimate the dynamic pattern on how tariff reductions affect county-level outcomes over years, this study follows the approach in [Dix-Carneiro and Kovak \(2017\)](#) with the specification in [Eq.5](#). $y_{i,1998}$ refers to the initial outcomes in 1998. $\Delta \widehat{CIT}_{i,1998,t-1}$ and $\Delta \widehat{COT}_{i,1998,t-1}$ index the changes in tariff between the year $t - 1$ and 1998 in county i . This equation is estimated separately for each year $t \in [2000, 2008]$ as reflected by the t subscripts. As each regression is at cross-sectional level, province fixed effect ρ_p is controlled for robustness. The coefficient of interests, β_0 and β_1 , present the cumulative effect of trade openness on outcomes by year.

$$y_{i,t} - y_{i,1998} = \alpha + \beta_0 \Delta \widehat{CIT}_{i,1998,t-1} + \beta_1 \Delta \widehat{COT}_{i,1998,t-1} + \rho_p + \varepsilon_{i,t} \quad (5)$$

The changes in outcome and trade liberalization vary with the year t , implying the coefficient β_0 and β_1 reflect the continuous evolution on the county-level measure of tariff reduction during the whole sample period. Compared to the other literature examining the regional or industrial effects of trade shocks, this approach only captures the relative effects across regions (counties) ([Autor, Dorn and Hanson, 2013](#); [Dix-Carneiro and Kovak, 2017](#)).

The dynamic pattern on light density is displayed in [Figure 5](#). The estimated results for coefficients β_0 and β_1 in [Eq.5](#) are plotted for each year by solid lines with 95% confidence intervals (dashed lines). The vertical lines indicate the year 2001 when China joined

the WTO. As the independent variables on tariff differences are lagged for one year, the coefficients are presented for the period 2000 to 2008. Both sub-figures show that the local economic effects of liberalization have already appeared before China's WTO accession and remained a steady trend. **Figure 5 (a)** presents the dynamic pattern of input tariff reductions. The negative coefficients confirm the findings that input tariff reduction would lead to an increase in local economic development. However, the effects are approximately statistically insignificant during the first three years since China joined the WTO. After these three years, the impacts of input tariff reduction became positive and statistically different from zero, and the magnitude of the estimators didn't change a lot over time. It indicates that a county did not really benefit from input tariff cuts in the early years when China joined WTO, although it could steadily gain from it since 2004. The width of the 95% confidence interval was narrowing from 200 to 2008, also implying that the local economy became more specialized in benefiting from the production cost cuts. **Figure 5 (b)** plots the dynamic pattern of the output tariff reductions. The estimated coefficient was positive and statistically significant in the first three years since China joined WTO, implying a negative impact of output tariff reductions on the local economy. However, the impacts became statistically indifferent from zero and smaller since 2004.

>>> **Figure 5** Here <<<

The findings on dynamic pattern extend the understanding of the effects of tariff reductions on the regional economy, especially featuring the trade adjustment process in the context of China. The local economy did not swiftly capture the benefit from lower input costs, which was induced by input tariff reduction. While the negative effect of import competition on final goods appeared more quickly. The adjustment to the trade process lasted for three years and then the effects became relatively steady. The interpretations could be built from the previous studies which suggest the mechanisms from the labor market, including the slow responses of local outcomes to tariff changes, the imperfect labor mobility as well as the dynamics in labor demand ([Bound and Holzer, 2000](#); [Autor, Dorn and Hanson, 2013](#); [Dix-Carneiro and Kovak, 2017](#)).

Overall, reductions in input tariff lead to an increase in the local economy. The in-

terpretation for this result can be quite clear and straightforward: lower tariffs on inputs implies a lower cost for local industrial production, which have positive impacts on economic development. Findings from firm-level studies also support a similar pattern. For example, [Amiti and Konings \(2007\)](#) and [Goldberg et al. \(2010\)](#) found that lower input tariffs led to an increase in domestic industrial products in the developing Indonesia and India, respectively.

Before proceeding, it is useful to place the magnitude of the estimates from the benchmark specification in context: The results suggest that a 1% decrease in input tariff can contribute a 0.9~1.5% increase in the local economy. Since the input tariff rates reduced about 6% on average during 1998 to 2008, the accumulated contribution of tariff reduction on the development of counties in China can reach 5.4 ~ 9.0%.

5.2 Effects on County-level Emission

Next, I examine the effects of input and output tariffs on the county-level pollutant emissions ([Table 4](#)). Three types of key representative pollutants are selected, COD, SO₂, and NH₃-N.

[Table 4](#) reports the results. Empirical results in columns (1), (3) and (5) investigate the average treatment effect of tariff reductions on the emission amount of three representative pollutants. Columns (2), (4) and (6) apply per capita emission as outcomes, which is defined as the emission amount over the county's population. County fixed effects and year fixed effects are included in all regressions. The robustness of these results are tested by clustering the standard errors at two different levels, and the results show that conclusions do not change.

>>> [Table 4](#) Here <<<

For the impacts of tariffs on the total amount of emissions, the coefficients from columns (1), (3) and (5) suggest that the reduction on input tariff leads to lower levels of emission, but the impacts from the output tariff reduction are opposite. All the coefficients are statistically significant: 1% decrease in input tariff rate can increase pollutant emission by

3.7~5.5%, while a 1% decrease in output tariff rate can reduce the emission by 1.1~2.2%. The heterogeneous impacts of tariff reductions on different pollutants are not evident, but the power of input tariff is stronger than output tariff when comparing the coefficients of each pollutant.

For per capita emission, empirical results in columns (2), (4) and (6) indicate that the reduction on input tariff lower the emission of all three pollutants, while the impacts of output tariff reduction are the opposite. The statistically significant coefficients suggest roughly heterogeneous impacts of tariffs on different pollutants: for COD and SO₂, a 1% reduction on input tariff leads to a 1.8~2.2% decrease on per capita emission, which is about two times larger than the impacts of input tariff on NH₃-N. Similarly, a 1% output tariff rate reduction can increase the per capita emission of COD and SO₂ by 0.6%, but its impact on NH₃-N decreases to 0.3%.

Overall, the reduction in input tariff rate would lead to emission reductions while output tariff rates have the opposite impact. The effects of the input tariff reduction imply a lower production cost could lead to a lower total amount of emission. And the effects of the cuts in output tariff suggest a more competitive domestic market would make more emission. This result can be explained in several possible ways, but the key point is where the pollutants come from ([Cherniwchan et al., 2017](#)). On the one hand, if the pollutant is mainly generated by inputs which are originally produced domestically, the input tariff reduction on these intermediates could spur the firms to import these polluted products from the rest of the world rather than producing the pollutant domestically. Thus the total amount of emission and per capita emission decrease due to the cheaper polluted inputs. However, this effect is highly relying on what kind of tariff has declined, implying more complex heterogeneous impacts of the tariff reductions. For example, if most of the input tariff reductions occur in cleaner intermediates, the domestic firms might tend to produce more polluted inputs. On the other hand, if the output tariff reduction makes the domestic market more competitive and the imported products are more high-tech with a cleaner production process, the domestic firms may (1) choose to produce more dirty inputs to lower their cost of production to make themselves more competitive, or (2) change their industrial structure to produce the goods with comparative advantage but attached with

more pollutants. As this study addresses the context of China, which is featuring on processing trade with a great number of pollutant emissions, the traditional Ricardian model suggests it will produce more on these polluting goods, supporting the mechanisms on (1) and (2) (Costinot, Donaldson and Komunjer, 2012; Costinot et al., 2015). Additionally, many firm-level studies focused on China have confirmed the pattern that a more competitive market induced by trade liberalization could help promote productivity, upgrade technology, and improve the product quality (Fan, Li and Yeaple, 2015; Brandt et al., 2017; Fan, Li and Yeaple, 2018). The increased productivity and upgraded technology possibly imply the reductions in the per capita emission and the use of dirty inputs (Porter and van der Linde, 1995). However, the findings on the output tariff suggest that the improved productivity does not necessarily promise a cleaner production process, while the local economy is more likely to produce more polluted final goods according to its comparative advantage.

As spill-over effects may confound the benchmark results that the counties' tariff reduction could affect each other especially their neighbor, we construct other two tariffs for each county to address the spill-over effects: neighboring tariffs on inputs and outputs. The neighboring tariffs are weighted by each county's industrial output. Table 5 reports the results. The independent variables $Input\ Tariff_{Neighbor}$ and $Output\ Tariff_{Neighbor}$ indicate the aggregated neighbor's tariffs, while the other two variables are the county's tariffs. In columns (1), (3), (5), (7), we only include the neighbor's tariff. In other columns we further include the county's own tariff. All the coefficients for neighbor's tariff are not only statistically insignificant but also very small, while the coefficients for county's own tariffs remain the same signs and statistically significant. These results therefore exclude the concern on spill-over effects.

5.3 The Gains from Trade

I now put together the results from the previous two subsections and discuss their implication for the gains from trade in China. During the sampled period, the county-level input and output tariff reduced 6.2% and 9.8% on average. The biggest cuts on input tariff reached 21.8% and the maximum value for output tariff rate reduction is 60.5%. As

mentioned above in [section 2](#), there are a few counties underwent an increase in tariffs: the minimum value for county-level input and output tariff reductions are -3.0% and -15.6%, respectively.

>>> [Figure 6](#) Here <<<

[Figure 6](#) shows the gains on economic growth for counties with respect to their tariff reductions during the study period. The light pink area indicates the regions with no data, and the blue color displays the changes in the proportion of the nighttime light density for each county. As the map indicates, most of the counties benefited 0~10% growth due to the tariff reductions during 1998 to 2007. The spatial differences are not very obvious, and there is not significantly different impact on border or coastal regions. The county that benefited most from tariff reductions is located in the central of China, and its nighttime light density increased 23.9% due to the falling trade barriers. On average, the nighttime light density improved about 6.8% for all displayed counties.²⁴

>>> [Figure 7](#) Here <<<

[Figure 7](#) plots the gains on regional emissions from 1998 to 2007. The regions with no data are shown in light green. The redder regions imply more increase in the measurement of total amount emission and per capita emission, while the purpler indicates a larger decline in the measurement of emissions. All four maps show that there are very a few counties lost from trade regarding emissions. Although it slightly illustrates that west of China seemed to benefit more from the trade, the spatial difference is still evident enough.

>>> [Figure 8](#) Here <<<

By aggregating the county-level gains at the national level, we can derive the yearly total amount of gains from Trade for China. [Figure 8](#) shows the gains from trade for China during 1999 to 2007. The nation-level tariff reductions on input and output are calculated from the simple unweighted average of the tariff rates at the product level.

²⁴The declines in night light density induced by trade shocks only happened in 17 counties, and the minimum value for the growth rate is -3.3%.

In [Figure 8](#), I examine the impacts from trade shocks on nighttime light density (solid black line), total amount of emission of COD and SO₂ (dashed blue line and dashed green line, respectively), and per capita emission of COD and SO₂ (solid yellow line and solid purple line, respectively). Although the parameters vary across different outcomes, the aggregated impacts from both input and output tariff reductions look similar. The time pattern of the gains follow the tariff reduction trend as shown in [Figure 2](#), implying a larger change in tariffs is related to the bigger impact on gains. Especially in 2002, when China experienced the largest cuts in tariff during the study period, the tariff reductions could contribute 2.9% in economic growth, and reduce the total amount of COD and SO_{2.5} emissions by 7.2% and 5.1%, respectively.

6 Mechanisms

Our empirical findings display the different impacts of input and output tariff reductions on county-level socioeconomic and environmental performance. For its impacts on economic development, it can be interpreted that input tariff reductions lead to lower cost for production hence the light density (a proxy for per capita GDP) and the number of lights (proxy for GDP) increase. We further provide evidence on the adjustment process to show that output tariff reduction indeed made negative impacts on economic growth, while this impact became insignificant after a medium-term adjustment. Previous studies have documented various underlying mechanisms, including slow responses of local outcomes to tariff changes, the imperfect labor mobility as well as the dynamics in labor demand (Bound and Holzer, 2000; Autor, Dorn and Hanson, 2013; Dix-Carneiro and Kovak, 2017).²⁵

We explore and highlight the underlying channels on how tariff reforms affect emission and ambient in this section. In practice, we evaluate three mechanisms, including scale, composition and technique effects, the composition of tariffs, and the Pollution Haven Hypothesis. To do so, we first present a statistical decomposition of the pollution emissions using county-level data from 1998 to 2008. Thus the information can be used to illustrate whether changes in the total scale of output or changes in the composition of the output shares are able to explain the observed reductions in emissions. In particular, we focus on the county-level decomposition rather firms or products are unique to the firm-level studies and is meant to capture the more aggregated effects. Second, to quantitatively estimate the impacts of the decomposed factors, we regress the emission on the interactions between the tariff and initial technology, composition, and scale status.

To separately examine whether different types of tariff reductions have heterogeneous impacts, we further map the tariffs into polluted and clean industries. As the benchmark results indicate that input tariff reduction provides cheaper clean inputs to local production. This approach allows us to explore the channel through a supply chain perspective

²⁵We do not explore or confirm any mechanisms about trade adjustment regarding economic growth, as this work features the impacts of trade shocks on environment and we do not have enough data on employment and capitals. More importantly, the channels on how tariff reductions affect the local economy is more intuitive.

(Wang et al., 2018). Finally, we test the popular theory in environmental economics, Pollution Haven Hypothesis (PHH), to integrate the economy and environment characteristics into the same framework. As our data can link the detailed information on the economy and environmental quality, it allows us to investigate whether PHH holds in the context of China.

6.1 Technique, Composition, and Scale effects

Many previous studies interpret the national changes in the total amount of pollutant emissions via industrial/product- or regional level decomposition.²⁶ Both decomposition works illustrate the changes in emissions by three sources: the overall size of the economy (scale effect), the mix of outputs comprising the economy (composition effect), and the technologies employed in production and abatement (technique effect) (Copeland and Taylor, 1994; Grossman and Krueger, 1995). The industrial/product- and regional level decompositions only differ in exploring the composition effect. For industrial/product-level decomposition work, the composition refers to the product or industrial structure (i.e., the share of each product/industry's output in terms of the total amount of output). For regional level decomposition, it addresses each region's share of output, featuring the transfer of scale of the economy across the regions.

Levinson (2009) and Shapiro and Walker (2017) found that most of the pollution reductions in the U.S. have come from changes in technology, and the changes in composition can also contribute to the declines in the total amount of emissions. In the context of China, Auffhammer et al. (2016) decomposed the CO₂ emissions at the city level. They found that scale effect contributes to rising CO₂ emissions, while the technique effect leads to declining CO₂ emissions in all cities. The composition effect leads to increasing CO₂ emissions in the third-tier cities, while it reduces CO₂ emissions in the first and second-tier cities, due to the relocation of energy-intensive industries from the latter to the former type of cities.

²⁶See, for example, Antweiler, Copeland and Taylor (2001); Cole and Elliott (2003); Levinson (2009); Auffhammer et al. (2016); Shapiro and Walker (2017).

Statistical Decomposition. To decompose the impacts of trade shocks into these three paths, the standard approach is to further estimate the changes in scale, composition, and the technique induced by trade liberalization. For example, the tariff reductions can have different directions on changing the size of the regional economy, and the structure of the economy will change as each county might increasingly specialize in those activities in which it has a comparative advantage. Antweiler, Copeland and Taylor (2001) and Cole and Elliott (2003) found that trade-induced composition effect is small, and suggested the actual impact of the composition effect on the environment depends therefore upon the determinants of the region's comparative advantage. This study also makes an extension of this literature by exploring the impacts of trade on the decomposed factors in the context of China. In practice, I apply the regional level decomposition to changes in the reallocation of counties' share on production, where the composition here refers to the each county's industrial share to the whole country.

$$Z_t = \sum_i z_{i,t} = \sum_i x_{i,t} e_{i,t} = X_t \sum_i k_{i,t} e_{i,t} \quad (6)$$

Consider the following representation of total emission in Eq.6, denoting Z_t as the total emission in China in year t , Z_t equals the sum of emission from each county i , $z_{i,t}$. Alternatively, the each county's emission $z_{i,t}$ can be written as equal to its output (e.g., industry output) multiplied by a county-specific emission intensity factor $e_{i,t}$. The total emissions can also be represented by the total output shipped by all counties X_t , multiplied by the sum of each county's share of total output, $k_{i,t} \equiv x_{i,t}/X_t$, times an emission intensity coefficient reflecting pollution per output ($e_{i,t} \equiv z_{i,t}/x_{i,t}$). Totally differentiating then dividing through by Z_t yields three terms representing the scale, composition, and technique effects in Eq.7.

$$\frac{dZ}{Z} = \frac{dX}{X} + \frac{dk}{k} + \frac{de}{e} \quad (7)$$

By using Eq.7 with a balanced annual data from 1998 to 2008, we take the decomposition on COD and SO₂ emissions in China. Figure 9 illustrates the resulting statistical

decomposition for two pollutants, and both of them have similar patterns. We scale total output so it equals to 100 in 1998. The bottom solid-green line depicts the actual observed emissions trends, which consists of changes to both the scale, composition, and techniques associated with production since 1998. During the studied period, the total amount of COD emission decreased about 45% while the SO₂ increased about 144%. The general trends of COD emission keep decreasing, and there is a break point for SO₂ in 2006 when China adopted a brand-new nationwide tighter environmental policy. The median dashed-blue line represents plots the counterfactual for what emissions would have looked like with the same composition share of county-level industrial output as was observed in the base year, 1998. It implied that if the county-level emission intensity and share of the county's output have not changed, the COD and SO₂ emission would have kept increasing to 421% and 438%, respectively. The top dashed-red line summarizes the emission levels with a fixed technique level in 1998. It suggests that the COD and SO₂ emissions will increase about 611% and 753%, respectively.

>>> **Figure 9** Here <<<

The gap between the solid line and dashed lines show the differences between the counterfactual and actual emission. These results suggest both changes in composition (share of county's output) and scale lead to emission increase in the context of China.²⁷

The statistical decomposition leads to several conclusions. On the one hand, industries or polluted production were transferred from lower emission intensity counties to higher ones during the studied period, when comparing the scale effect and scale and composition effect. It implies that counties with dirtier techniques produced enjoyed more shares of outputs. On the other hand, the technique effects explain most of the emission reductions, which implies a great upgrading in technology during the studied periods.

To proceed the mechanisms that how trade openness affects the total amount of emissions through the scale, composition, and technique effects, I examine the results by adding

²⁷ [Auffhammer et al. \(2016\)](#) conducted a decomposition on China's city-level CO₂ emission from 1998 to 2009, and their results show a similar pattern that the scale and composition effect is slightly higher than the sole scale effect and make 300% increase in CO₂ emission. While in other countries, for example, the US, it is shown that the scale effect is higher than the scale and composition effect ([Levinson, 2009](#); [Shapiro and Walker, 2017](#)).

the changes in the three factors into the regression as dependent variables.

Scale Effect. In [section 5](#), the columns (3) and (4) of [Table 3](#) suggest that the input tariff reduction lead to increase in the scale of economy if taking the number of lights as a proxy, while the output tariff reduction has no statistically impact.²⁸ This result stands as the county-level scale of an economy can benefit from input tariff reductions.

>>> [Table 6](#) Here <<<

Composition Effects. To explore whether tariff reductions cause any transfers of the outputs across counties, [Table 6](#) reports this composition effect by adding the interaction term between the initial emission intensity in 1998 and the tariff reductions. [Eq.8](#) shows the econometric model for the regression, where $X_{i,1998}$ indexes the outcomes of county i in 1998. To more formally investigate the heterogeneous impacts, we restrict $X_{i,1998}$ to a dummy variable indicating the income group in 1998. $X_{i,1998} = 1$ if county i 's outcome in 1998 was above the median, otherwise $X_{i,1998} = 0$. Meanwhile, we control the group-year fixed effect for robustness. The number of lights, which perform as a proxy for the scale of economy, is the dependent variable in the regression. As the former decomposition results imply that polluted production was moved from lower emission intensity counties to higher ones, the coefficients of the interaction terms can capture this effect by providing the information on whether tariff reductions led to different economic outputs growth in initial more polluted counties.

$$y_{i,t} = \alpha + \beta_0 \widehat{CIT}_{i,t-1} + \beta_1 \widehat{COT}_{i,t-1} + \beta_2 \widehat{CIT}_{i,t-1} \cdot X_{i,1998} + \beta_3 \widehat{COT}_{i,t-1} \cdot X_{i,1998} + \rho_i + u_t + \varepsilon_{i,t} \quad (8)$$

As shown in [Table 6](#), panel A and B present the results for COD and SO₂, respectively. All the coefficients for the interaction terms between initial emission intensity and output tariff are statistically insignificant and very small, imply the output tariff reduction has no

²⁸We don't directly use industry output as the measure of scale for two reasons similar to the county-level data on GDP: (i) the county-level CPI data to deflate the output values is unavailable; (ii) the county-level industry output data is not randomly missing. [Table A.4](#) reports the cross-validation results on the industrial output and number of lights.

composition effect on both pollutants. For the interaction terms between initial emission intensity and input tariff, the coefficients are negative and some of them are statistically significant for SO₂. It suggests that input tariff reductions would lead to more economic growth in a county with higher emission intensity in 1998, which could increase the total emissions for the whole nation. As the reported coefficients only range from -0.014 to -0.013, which is small. It is similar to [Antweiler, Copeland and Taylor \(2001\)](#) and [Cole and Elliott \(2003\)](#) which found that trade-induced composition effect could only create small-scale changes in pollution.

Technique Effects. As examined in [Table 7](#), we test the technique effects by estimating the impacts of tariff reductions on emission intensity measured by emission per number of lights. This result is consistent to our findings from the columns (2), (4) and (6) of [Table 4](#), where the emission intensity is measured by the total amount of emissions over population. Both results provide information on how trade shocks link to changes in technology upgrading or abatement. Consistently, they imply that tariff reduction can decrease the emission intensity for these representative pollutants. However, the impacts of output tariff are the opposite.

>>> [Table 7](#) Here <<<

Overall, several conclusions stand out by investigating the effects of technique, composition, and scale on pollutants accompany with trade liberalization. In the benchmark results, it is found that the input tariff reductions could lead to decrease the total amount of pollutants, while the decrease in output tariff increases the emissions. First, the input tariff reductions could increase the emission by increasing the scale of economy, while output tariffs have no statistically significant scale effect. Second, the cuts in input tariff could reduce the emission by composition effect, as the reductions on input tariff could lead to less growth in scale of economy in a county with higher emission intensity in 1998. Additionally, the composition effect induced by tariff reduction is very small. The result also indicates that output tariff has no statistically significant composition effect. Third, input tariff reduction could lead to declines in emission intensity, and the impacts of output tariff are the opposite. Fourth, for input and output tariff, the results show no evident

heterogeneity across COD and SO₂. To conclude, the input tariff reductions could affect emission by different directions, while output tariff reduction increases the emission by decreasing the emission intensity (technique effect). For cuts in input tariff, it can, on the one hand, increase the emission by raising up the scale of economy, and on the contrary decrease it by a small composition effect and reducing the emission intensity (technique effect).

6.2 Composition of Tariff Reductions

The impacts of tariff-induced liberalization could be attributed to the heterogeneous cuts in tariffs across products or industries (Cherniwchan et al., 2017). For example, if the output tariff cuts mainly happen in steel, which will make external pollution emissions during the process of domestic production. The lower import tariff of steel could lead more imports on it while less produced domestically, implying a reduction on emissions. To explore this channel that whether different sources of tariff reductions lead to differing in their effects on the emissions, I further decompose the tariffs attached to pollutant-specific industries. The tariff for pollutant-related industries (hereafter ‘tariff for pollutant-related industries’) features the tariff rates changes in pollutant-related industries, while the tariff for other industries (hereafter ‘tariff for other industries’) refers to the changes in other industries. For example, if the manufacturing’s production could emit COD, then we define this manufacturing as a COD-related industry.

In practice, this construction of these tariffs applies the same strategy in Eq.1. The industrial level tariffs on inputs and outputs follow the first and second steps in section 2, which can be uniquely identified by 4-digit cic code. Next, I manually classify the types of the industry into pollutant-specific sectors. Each pollutant’s (COD and SO₂) related industries is defined from the First National Census of Pollution Sources. This data documents each industry’s emitted pollutants. For example, the COD-specific industries are the industries whose emission inventory includes the COD. After matching the types of each industry, I separately compute each county’s aggregated industrial outputs from pollutant-specific industries. Each industry is only calculated in its industrial classification. As shown in Eq.9, $CT_{i,t,c}$ represents the county-level weighted average tariff of

industrial type c for county i in year t . c refers to pollutant-specific industries. $S_{i,s,t,c}$ indicates to the industrial output of all the industrial s, t for county i in year t ; $S_{i,t,c}$ is the total industrial output of type c for county i in year t ; $T_{s,t}$ indexes the tariff for industry s in year t . In practice, the county-level input tariff for pollutant-related industries and other industries, and output tariff for pollutant-related industries and other industries are calculated separately as $CITp_{i,t}$, $COTp_{i,t}$, $CITc_{i,t}$, $COTc_{i,t}$.

$$CT_{i,t,c} = \frac{\sum_{s,c} S_{i,s,t,c} T_{s,t}}{\sum S_{i,t,c}} \quad (9)$$

Separately examining the impacts of the above mentioned four tariffs on environmental performance can help shed light on the channels on how import tariffs on pollutant-related industries matter. As the benchmark results suggest that reduction in input tariff can lower both the total amount of emission, it implies that regional producers can directly buy the polluted intermediates abroad rather than producing it domestically. On the other hand, the benchmark results also indicate that a more competitive market induced by output tariff reduction can cause more local emission. It suggests a channel through the comparative advantage that local producers have to choose a more polluted production process to increase their competitiveness. Both above mentioned regional producers refer to polluted industries, of which their production could generate pollution.

Taking the above message, it is expected that the input tariff reductions on local polluted industries could reduce the emission as they would have better access to polluted inputs abroad. However, the reduction in output tariff for pollutant-related industries is expected to increase the emission as the local polluted industries might choose a polluted production process to make them more competitive in the market. On the other hand, for tariff reductions on other industries, its impacts might be more complex. Lower input tariffs on other industries can make the local pollutant-related industries less competitive. As a result, the pollutant-related industries have to choose more polluted production process to lower their cost. However, lower input tariffs on other industries might also reduce the local emissions. For example, the pollutant-related industries might transfer to clean sectors driven by profits. In order to explore whether it is the composition of the tariff

reductions affect the regional emissions, we run a series of regressions of the following form in Eq.10.

$$y_{i,t} = \alpha + \beta_0 CITp_{i,t-1} + \beta_1 COTp_{i,t-1} + \beta_3 CITc_{i,t-1} + \beta_4 COTc_{i,t-1} + \rho_i + u_t + \varepsilon_{i,t} \quad (10)$$

Table 8 reports the results from Eq.10 for COD and SO₂ which include different types of tariffs as dependent variables. In columns (1) and (4), I only put the tariffs on pollutant-related industries into the regression. For comparison, columns (2) and (5) only include the tariffs on other industries. And in columns (3) and (6), all four types of tariffs are included. For COD, it indicates that a 1% reduction in production cost (input tariff) for pollutant-related industries could lead to 1.8~2.4% decrease in total amount of COD emission. The coefficients for output tariffs on pollutant-related industries are negative and statistically significant, implying that a more competitive domestic market would cause the regional polluted industries to enhance their competitiveness by applying a more polluted production process. All coefficients for tariffs on other industries are statistically insignificant, suggesting that the tariff changes in other industries do not affect the COD emissions as these industries' production does not relate to COD. For SO₂, the coefficients for input and output tariffs on other industries are statistically insignificant, too. Its coefficients on tariffs of pollutant-specific industries are insignificant but mostly remain the signs as COD, implying that both cheaper inputs and the more competitive market could possibly have consistent channels to both pollutants.

>>> Table 8 Here <<<

Overall, it is confirmed that the composition of tariff reductions could affect emissions in different ways. On the one hand, the inputs tariff reductions help regions to import more polluted intermediates rather than producing it domestically; on the other hand, the output tariff reductions make the polluted industries to be more polluted as an approach to be competitive in a more open domestic market.

6.3 Pollution Haven Hypothesis

In this section, we present the results to show whether the Pollution Haven Hypothesis is observed during the trade liberalization process in China. In a conventional trade theory, it is suggested that input tariff reductions lead to lower cost for production while output tariff reductions increase the competition in the domestic market. Both lower production cost and the competitive market might spur regions to specialize in productions in which they have a comparative advantage. Additionally, counties at different levels of economic conditions may have different comparative advantages. The Pollution Haven Hypothesis suggests that low-income regions can have a comparative advantage in producing polluted goods as they may have less restrictive regulations on polluting industries than what the high-income counties have. As a result, the trade liberalization may affect the local economy and environment by relocating the economic structures between counties.

To test PHH, we integrate the economy and environment into the regression by adding an interaction term between tariff and initial light density in 1998, which represents the initial county-level income. To formally estimate this heterogeneous impacts, we divide two income groups and assign them with a group dummy variable *Income Group*₁₉₉₈. For robustness check, we also control for the income group-year fixed effects. In practice, *Income Group*₁₉₉₈ = 1 if county *i*'s light density in 1998 was above the median, otherwise = 0. Performances on emissions and economic characteristics are included as my outcomes of interests. The coefficients of input tariff and its interaction term provide the information on Pollution Haven Hypothesis that how lower trade cost and a more competitive market affect counties with different initial income level in different ways.

Table 9 provides the corresponding regression analysis on how initial income-level affect environmental performance. In regressions, the interaction terms are the initial light density group in 1998, which indicates a dummy variable. Each regression controls for county fixed effect and the income group-year fixed effect. For robustness check, we additionally control for province-year fixed effects in even columns. For the regressions with the income group dummy, they additionally include the income group-year fixed effect. The coefficients of the interaction terms indicate the information about the heterogeneous

impacts of trade shocks on counties with respect to their initial economy status.

>>> **Table 9** Here <<<

For the heterogeneous impacts of input tariff reductions, the coefficients for both input tariff and the interaction terms are positive to all the measurement of pollutants, including COD and SO₂, and some of the interactions are statistically significant. The results indicate that (i) input tariff could lead to declines in pollutants on average in both poor and rich counties, (ii) initial rich counties underwent more environmental quality improvement compared to initial poorer ones. This pattern is consistent with the pollution haven hypothesis that lower production cost could shift pollutants to poorer regions due to comparative advantage. However, as most of the coefficients are not statistically significant, our results only suggest a weak pattern of pollution haven in terms of input tariff reductions and changes in the environment.

For output tariff reductions, the coefficients for the interaction terms between output tariff and income group dummy are positive for measures on emissions. The signs of the interaction terms and output tariff are opposite, suggesting that the impacts of output tariff cuts might go on two different directions for poor and rich regions. For example, the results imply that a 1% cuts in output tariff can increase 0.1% and 1.3% total amount of emissions of COD in initial rich and poor counties, respectively (column (1)). Columns (5) and (7) confirm the different directions of impacts of cuts in output tariff on two groups: a 1% output tariff decline could lead to 0.4% reductions of the total amount of SO_{2.5} emissions in the initial richer county, while 1.3% increase in poorer one. Although many coefficients are small and insignificant, the pattern of output tariffs is still consistent with a weak PHH.

>>> **Table 10** Here <<<

On the other side, **Table 10** reports how initial income-level affect the economic performance, where the outcomes of interests are different measures on the economy, including light density, number of lights, and per capita lights. The light density and per capita lights are viewed as proxies for per capita GDP, and the number of lights for GDP. First,

all coefficients for output tariff and its interaction term are very small and statistically insignificant, implying output tariff reductions have neither average treatment effects nor heterogeneous impacts on the local economy. Second, all coefficients for input tariff and its interaction term are positive and negative, respectively. By comparing the coefficients, for example, it is found that a 1% cuts in input tariff could lead to 0.6% and 0.9% growth in initial rich and poor counties, respectively. This pattern is consistent with the predictions of PHH. Third, the coefficients for the interaction terms between input tariff and income group dummy remain statistically insignificant, implying the PHH pattern is very weak.

7 Conclusion

The debate over trade liberalization especially worries its consequences on economic growth and the environment. This study directly answers this question in the context of China and assesses several alternative explanations for the underlying channels. In particular, this paper focuses on import tariff reduction induced trade openness process and divides the import tariff as two kinds of trade shocks on county-level inputs and outputs.

First, using 11 years of most comprehensive county-level data on socioeconomic and environmental performances, our analysis reveals that local economic development can benefit from tariff reduction on inputs, while output tariff reduction on output shows no statistically significant impacts. On the other hand, tariff reduction on inputs decreases both total amounts of pollutant emissions and the emission intensity at county-level, while tariff reduction on outputs does the opposite.

Second, the explanation of the tariff reductions and economic growth is straightforward: lower tariff rate on inputs implies a lower production cost, hence promoting the economic development. Our estimates suggest that (1) on average, 1% decrease in tariff on inputs leads to 0.9~1.5% economic growth, (2) in the context of China, the tariff reduction on inputs from 1998 to 2008 contributes to 5.6~9.3% economy development on average.

Third, we evaluate the gains from trade of China at both county level and aggregated national level. Our estimates speak to the *cost* and *benefit* from tariff reforms. The input tariff reductions during 1998 to 2008 benefited China through not only lowering the price of inputs but also providing more access to clean intermediates. Although cuts in output tariff would harm the local economy and environment, the greater impacts of input tariff cuts overall bring about a more positive influence from trade liberalization.

Fourth, we begin our explanation on the consequences of tariffs on environmental performance with a statistical decomposition which shows that (1) the polluted production or polluted industries were moved from counties with relatively lower emission intensity to higher ones, implying a potential explanation on Pollution Haven Hypothesis; (2) the

reallocation of the share of industry outputs cannot explain the fall in pollution emissions; (3) the technique effects dominate the improvement on total amount of emissions.

Next, we link the trade shocks to the scale, composition, and technique effects to further explore the role of trade openness in the above-mentioned processes. These channels illustrate impacts of input tariffs through scale and technique effects in different directions, while output tariff only affects the emissions through technique effects. We further dig into different types of tariff reductions. Our results confirm that the regional environment benefit from lower production cost as polluted industries could choose to use cleaner and cheaper inputs. On the other hand, to enhance their competitiveness through comparative advantage, in a more competitive market, polluting industries often tend to pollute more.

Finally, we integrate the county-level economic and environmental characteristics on trade shocks to estimate the channels on Pollution Haven Hypothesis. Our results document a weak pattern of the PHH in the context of China: lower production cost leads to separate impacts on initial poor and rich counties. On the contrary, the influence from a more competitive domestic market induced by output tariff reduction is much smaller.

Our results have important implications for our thinking about the consequences of trade liberalization on a comprehensive framework regarding the economy and environment. First, this paper empirically confirms that China's trade openness can explain its great success in economic development during its accession to the WTO. Although import competition derived by output tariff reductions is viewed as a disadvantage for the domestic market, its impact does not appear in the context of China. Second, as the empirical findings show that input tariff reductions not only promote economic growth but also decrease the total amount of emission and emission intensity, it is primarily suggested to make the trade policy as a substitute for environment policy ([Copeland and Taylor, 2004](#)). Third, trade cost reductions are conventionally viewed as the reason for the greater economic divergence between rich and poor countries ([Pascali, 2017](#)). However, our results demonstrate that lower cost induced by cuts in input tariff could not only help economic development but also narrow the inequality by reducing the income gaps between the rich and poor regions, where such *cost* to narrow the economic inequality is a negative

impact on the environment. Finally, many firm-level studies suggest that a more competitive domestic market can promote a firm's productivity as well as the quality of the final goods ([Amiti and Konings, 2007](#); [Brandt et al., 2017](#); [Fan, Li and Yeaple, 2018](#)). However, our results suggest that this improvement in the productivity is not necessarily related to a reduction in the emission intensity or green technology upgrading. The firms might choose to use cheaper polluted producing methods to enhance its competitiveness.

Several worthwhile extensions could be further explored to this study. First, this study only focuses on aggregated impacts at the county level, but more detailed studies on firm level or product level may help explore more on the mechanisms. Second, a structure model integrating the trade shocks and local response on economy and environment can better explain the heterogeneous estimators reported in the results. This paper primarily explores several styled facts on the consequences of trade shocks, and a theory-based model is called for better economics interpretation. In addition, this paper links to series of literature focused on welfare gains from trade openness and the optimal trade policy. Does current trade openness make net welfare gain? Or what is optimal trade policy? We leave these extensions and questions for future work.

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Figure 1: Evolution of Imports in China

Notes: The solid blue line and dashed green line represent the trade volumes on intermediates and final goods in China from 1994 to 2008, respectively. The vertical red line indicates the year 2001 when China joined WTO. Trade volumes in 1994 is treated as the base of measurement. The trade volumes are deflated with the national Consumer Price Index. Data Source: National Bureau of Statistics (NBS) of China.

Figure 2: Evolution of County Level Import Tariff Reductions on Inputs and Outputs

Notes: The solid lines show the median county-level weighted average input and output tariffs, the shaded area (for output tariffs) and dashed lines (for input tariffs) show the interquartile range.

Figure 3: County-level Tariff Reductions

(a) Input Tariff Reduction 1998-2007

(b) Output Tariff Reduction 1998-2007

Notes: This figure plots the county-level reductions during the study period. The light green area indicates the regions with no data. The red areas display the changes in county-level tariffs.

Figure 4: Nighttime Lights of China in 1998 and 2008

(a) 1998

(b) 2008

Figure 5: Dynamic Pattern: Tariff Reductions and Light Density

(a) Input Tariff

(b) Output Tariff

Notes: This figure's solid line plots the individual regression coefficient from , where the dependent variable is the change in county-level log formal light density and the independent variables are the county-level input and output tariff reductions. The dashed lines display the 95% confidence intervals. Each regression controls the province fixed effects. The standard errors are clustered at county level.

Figure 6: County-level Nighttime Light Gains from Trade Liberalization

Notes: This figure plots the county-level gains on nighttime light density from trade liberalization. The nighttime light density acts as the proxy for regional economic performance. The light pink area indicates the regions with no data. The blue areas display the changes in the proportion of the nighttime light density outcomes.

Figure 7: County-level Emission Gains from Trade Liberalization

(a) COD Emission, Tons

(b) SO₂ Emission

(c) per capita COD Emission, kg

(d) per capita SO₂ Emission, kg

Notes: This figure plots the county-level gains on emission from trade liberalization. The light green area indicates the regions with no data. The orange areas display the changes in the proportion of the emission outcomes, including the total amount of pollutants and per capita emission.

Figure 8: The China's Gains from Trade on Economy and Environment

Notes: This figure shows the gains from trade shocks for China between 1999 and 2007. Each year's gains are computed by unweighted average product-level tariff and the estimated parameters.

Figure 9: Emissions Statistical Decomposition in China

(a) COD Emission

(b) SO₂ Emission

Notes: This figure plots the observed and counterfactual trends in emissions for two representative pollutants based on the statistical decomposition from Eq. 7. The dashed blue line of each panel plots the counterfactual for what emissions would have looked like with a same techniques of production as was observed in the base year, 1998. The dashed red line represents what emissions would be looked have looked like if we maintained the same production techniques (defined as emissions per unit of output) and the same composition share of county-level industrial output as in the base year, 1998. The solid line represents the actual observed emissions trends, which consists of changes to both the scale, composition, and techniques associated with production since 1998.

Table 1: Determinants of Changes in Tariff Reductions

	Change in Tariffs from 1998 to 2007 (Tariff ₂₀₀₇ - Tariff ₁₉₉₈)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Night Light Intensity ₁₉₉₈	0.005 (0.013)	-0.031 (0.042)				0.054 (0.068)	-0.156 (0.104)	-0.159 (0.250)
(Night Light Intensity) sq. ₁₉₉₈		0.001 (0.001)						0.002 (0.006)
ln(Number of Lights) ₁₉₉₈			0.412* (0.246)	3.400* (1.853)			0.519 (0.512)	5.008* (2.910)
ln(Number of Lights) sq. ₁₉₉₈				-0.199* (0.117)				-0.320 (0.247)
ln(per capita Lights) ₁₉₉₈					-0.364 (0.489)	-0.442 (0.511)		-0.299 (3.223)
ln(Population) ₁₉₉₈							1.881 (1.702)	17.097 (20.139)
ln(Area) ₁₉₉₈							-0.892 (0.563)	-2.254 (2.853)
ln(Population) sq. ₁₉₉₈								-15.210 (11.149)
ln(Area) sq. ₁₉₉₈								0.079 (0.190)
City FE	Y	Y	Y	Y	Y	Y	Y	Y
R-Square	0.22	0.22	0.22	0.22	0.26	0.26	0.26	0.27
Obs.	2400	2400	2400	2400	1708	1708	1708	1708

Notes: This table estimates the relationship between the changes in county-level tariffs and initial social and economic characteristics in 1998. Standard errors in parentheses are clustered at the county level. * $p < 0.05$,

** $p < 0.01$, *** $p < 0.001$.

Table 2: County-level Summary Statistics (1998-2008)

	Observations (1)	Mean (2)	Min (3)	Max (4)	Std. Dev. (5)
<i>Panel A. County-level Trade Openness Index</i>					
Input Tariff (%)	26684	8.64	0.00	26.34	3.64
Output Tariff (%)	26684	14.28	0.00	63.70	8.40
Max. Input Tariff (%)	26684	9.04	0.00	26.34	3.55
Max. Output Tariff (%)	26684	14.80	0.00	63.70	8.53
<i>Panel B. Emission and Pollution Measurement</i>					
Chemical Oxygen Demand (COD, 10 ³ ton)	16751	1.88	0.00	86.16	42.96
Sulfur Dioxide (SO ₂ , 10 ³ ton)	16994	4.56	0.00	326.23	11.51
Ammonia Nitrogen (NH ₃ -N, 10 ³ ton)	11879	0.14	0.00	1.75	0.47
<i>Panel C. Socioeconomic Characteristics</i>					
Population (10 ³)	22712	460.17	5.60	2239.10	337.91
GDP (Million Yuan)	22656	4022.66	1.00	153000	6371.18
Nighttime Light Density	29370	8.18	0.00	63.00	13.12
Number of Lights	29359	4499.69	5.99	127987.84	5117.81

Notes: This table reports the summary statistics on key variables at county level from 1998 to 2008. Data in different panels are collected from different sources. The GDP data are not deflated over time. In practice, I apply the nighttime data as proxy for GDP.

Table 3: Effect of Tariffs on the County-level Socioeconomic Performance

	ln(Light Density)		ln(Number of Lights)		ln(per capita Lights)	
<i>Panel A. OLS Estimation</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff	-0.014*** (0.003)	-0.010*** (0.003)	-0.015*** (0.003)	-0.012*** (0.003)	-0.012*** (0.004)	-0.009** (0.004)
Output Tariff	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y	
Province-Year FE		Y		Y		Y
R-Square	0.99	0.99	0.96	0.97	0.93	0.95
Obs.	29433	29432	29433	29432	21158	21158
Number of Counties	2756	2756	2756	2756	1981	1981
<i>Panel B. IV Estimation</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff	-0.012*** (0.003)	-0.010*** (0.003)	-0.014*** (0.004)	-0.011*** (0.003)	-0.012*** (0.004)	-0.009** (0.004)
Output Tariff	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y		Y		Y	
Province-Year FE		Y		Y		Y
R-Square	0.99	0.99	0.96	0.97	0.93	0.95
Obs.	29433	29432	29433	29432	21158	21158
Number of Counties	2756	2756	2756	2756	1981	1981

Notes: This table estimates the effect of input and output tariffs on county-level socioeconomic performance. The nighttime light data are used as proxies for the socioeconomic indicators. In Panel B, the instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. Both independent variables (input tariff and output tariff) are lagged for one year. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Effect of Tariffs on the County-level Pollutant Emission

	COD (Tons, log) (1)	COD (per capita kg, log) (2)	SO ₂ (Tons, log) (3)	SO ₂ (per capita kg, log) (4)	NH ₃ -N (Tons, log) (5)	NH ₃ -N (per capita kg, log) (6)
Input Tariff	0.046** (0.019) (0.020)	0.018** (0.008) (0.008)	0.037*** (0.012) (0.013)	0.022*** (0.007) (0.008)	0.055** (0.027) (0.027)	0.009** (0.004) (0.004)
Output Tariff	-0.011** (0.006) (0.006)	-0.006*** (0.002) (0.002)	-0.011*** (0.004) (0.004)	-0.006*** (0.002) (0.002)	-0.022*** (0.008) (0.008)	-0.003** (0.001) (0.001)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
R-Square	0.76	0.75	0.83	0.82	0.76	0.71
Obs.	16520	16520	16740	16740	11664	11664
Number of Counties	1911	1911	1914	1914	1791	1791

Notes: This table estimates the effect of input and output tariffs on county-level pollutant emission and its emission intensity. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. Both independent variables (input tariff and output tariff) are lagged for one year. I probe the robustness of estimates accuracy by clustering the standard errors at two different levels: (1) county level and (2) county and province-year level (multi-way clustering suggested by [Cameron, Gelbach and Miller \(2011\)](#)). These standard errors are respectively reported in the parentheses below the estimated coefficients. My preferred specification clusters standard errors at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Test for Spill-Over Effects

	COD (Tons, log)		COD (per capita kg, log)		SO ₂ (Tons, log)		SO ₂ (per capita kg, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input Tariff _{Neighbor}	-0.006 (0.013)	-0.011 (0.013)	0.005 (0.005)	0.003 (0.005)	-0.000 (0.008)	-0.005 (0.009)	0.004 (0.005)	0.002 (0.005)
Output Tariff _{Neighbor}	0.005 (0.005)	0.006 (0.005)	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.003)	0.001 (0.003)	-0.002 (0.002)	-0.001 (0.002)
Input Tariff		0.038* (0.021)		0.015** (0.008)		0.032** (0.013)		0.018** (0.008)
Output Tariff		-0.008 (0.007)		-0.004* (0.003)		-0.010** (0.004)		-0.004* (0.002)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
R-Square	0.76	0.76	0.76	0.76	0.83	0.83	0.83	0.83
Obs.	14372	14372	14372	14372	14581	14581	14581	14581
Number of Counties	1883	1883	1883	1883	1884	1884	1884	1884

Notes: This table estimates the spill-over effects. The independent variables Input Tariff_{Neighbor} and Output Tariff_{Neighbor} are the neighbor's tariff, which is weighed by each neighbor's industrial output. The other two independent variables are the county's tariffs on input and output. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. All independent variables are lagged for one year. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Test for Composition Effects of Trade Openness

	ln(Number of Lights)			
	OLS		IV	
Panel A. $\times$ Emission Intensity Group Dummy of COD in 1998				
	(1)	(2)	(3)	(4)
Input Tariff	-0.010 (0.007)	-0.008 (0.006)	-0.012 (0.007)	-0.009 (0.007)
Input Tariff * <i>Intensity Group</i> ₁₉₉₈	-0.009 (0.009)	-0.008 (0.008)	-0.006 (0.009)	-0.006 (0.008)
Output Tariff	-0.000 (0.002)	0.001 (0.002)	0.001 (0.002)	0.002 (0.002)
Output Tariff * <i>Intensity Group</i> ₁₉₉₈	0.001 (0.003)	0.001 (0.002)	0.000 (0.003)	0.000 (0.002)
County FE	Y	Y	Y	Y
Group-Year FE	Y	Y	Y	Y
Province-Year FE		Y		Y
Adjust-R Square	0.95	0.96	0.95	0.96
Obs.	18815	18814	18815	18814
Number of Counties	1978	1978	1978	1978
Panel B. $\times$ Emission Intensity Group Dummy of SO ₂ in 1998				
	(1)	(2)	(3)	(4)
Input Tariff	-0.005 (0.007)	-0.002 (0.006)	-0.006 (0.007)	-0.003 (0.006)
Input Tariff * <i>Intensity Group</i> ₁₉₉₈	-0.013 (0.008)	-0.014* (0.007)	-0.012 (0.008)	-0.013* (0.007)
Output Tariff	0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	0.003 (0.002)
Output Tariff * <i>Intensity Group</i> ₁₉₉₈	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
County FE	Y	Y	Y	Y
Group-Year FE	Y	Y	Y	Y
Province-Year FE		Y		Y
Adjust-R Square	0.95	0.96	0.95	0.96
Obs.	18815	18814	18815	18814
Number of Counties	1978	1978	1978	1978

Notes: This table estimates the effect of input and output tariffs on county-level number of lights with respect to the initial emission intensity in 1998. The number of lights act as a proxy for county-level scale of economy (output). The results on OLS and IV are both reported. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. Both independent variables (input tariff and output tariff) are lagged for one year. The emission intensity is calculated by total amount of emissions over number of lights. The interaction term *Intensity Group*₁₉₉₈ refers to a group dummy variable: *Intensity Group*₁₉₉₈ = 1 if the county's intensity is higher than the median intensity in 1998, = 0 otherwise. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Test for Technique Effects of Trade Openness

	COD		SO ₂	
	(Tons per Number of Lights, log)		(Tons per Number of Lights, log)	
Panel A. OLS Estimation				
	(1)	(2)	(3)	(4)
Input Tariff	0.013*** (0.005)	0.008* (0.005)	0.021*** (0.008)	0.013* (0.008)
Output Tariff	-0.005*** (0.001)	-0.004*** (0.001)	-0.006** (0.003)	-0.003 (0.002)
County FE	Y	Y	Y	Y
Year FE	Y		Y	
Province-Year FE		Y		Y
Adjust-R Square	0.71	0.72	0.76	0.78
Obs.	15153	15147	15371	15366
Number of Counties	1900	1900	1902	1902
Panel B. IV Estimation				
	(1)	(2)	(3)	(4)
Input Tariff	0.014*** (0.005)	0.009* (0.005)	0.028*** (0.009)	0.018** (0.008)
Output Tariff	-0.006*** (0.001)	-0.004*** (0.001)	-0.007*** (0.003)	-0.004 (0.003)
County FE	Y	Y	Y	Y
Year FE	Y		Y	
Province-Year FE		Y		Y
Adjust-R Square	0.71	0.72	0.76	0.78
Obs.	15153	15147	15371	15366
Number of Counties	1900	1900	1902	1902

Notes: This table estimates the effect of input and output tariffs on county-level emission intensity. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Regressions of Separate Measures of Tariffs on Emission

	Total Amount of Emission			per capita emission		
Panel A: COD	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff _{COD-related}	0.0238*** (0.0086)		0.0183* (0.0096)	0.0189*** (0.0065)		0.0150** (0.0071)
Output Tariff _{COD-related}	-0.0088*** (0.0028)		-0.0079** (0.0032)	-0.0066*** (0.0021)		-0.0057** (0.0023)
Input Tariff _{Other}		-0.0056 (0.0086)	-0.0062 (0.0087)		-0.0033 (0.0062)	-0.0039 (0.0063)
Output Tariff _{Other}		0.0034 (0.0040)	0.0035 (0.0040)		0.0024 (0.0029)	0.0026 (0.0029)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adjust-R Square	0.76	0.75	0.75	0.73	0.73	0.73
Obs.	15027	13985	13858	15027	13985	13858
Number of Counties	1885	1836	1815	1885	1836	1815
Panel B: SO2	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff _{SO₂-related}	-0.0031 (0.0114)		0.0008 (0.0117)	0.0050 (0.0095)		0.0080 (0.0097)
Output Tariff _{SO₂-related}	-0.0044 (0.0043)		-0.0038 (0.0044)	-0.0058* (0.0034)		-0.0051 (0.0034)
Input Tariff _{Other}		0.0104 (0.0078)	0.0063 (0.0080)		0.0086 (0.0065)	0.0061 (0.0067)
Output Tariff _{Other}		-0.0040 (0.0029)	-0.0014 (0.0029)		-0.0030 (0.0023)	-0.0012 (0.0024)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adjust-R Square	0.82	0.83	0.82	0.81	0.81	0.81
Obs.	14136	14998	13765	14136	14998	13765
Number of Counties	1792	1887	1772	1792	1887	1772

Notes: This table estimates the effect of input and output tariffs on county-level emissions. The independent variables' subscripts *COD-related* and *SO₂-related* represent the aggregated tariffs on the pollutant-related industries, respectively. The independent variables' subscripts *Other* indicates the aggregated tariffs on other industries. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. All independent variables are lagged for one year. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Effects of Trade Openness on Pollutants w.r.t Initial Economy Status

	COD (Tons, log)		COD (per capita kg, log)		SO ₂ (Tons, log)		SO ₂ (per capita kg, log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input Tariff	0.028 (0.023)	0.010 (0.023)	0.015* (0.009)	0.008 (0.009)	0.027* (0.014)	0.016 (0.013)	0.018** (0.008)	0.010 (0.008)
Input Tariff * (Income Group) ₁₉₉₈	0.080* (0.046)	0.042 (0.047)	0.005 (0.019)	0.001 (0.020)	0.004 (0.030)	0.026 (0.030)	0.000 (0.020)	0.013 (0.020)
Output Tariff	-0.013* (0.007)	-0.006 (0.007)	-0.008*** (0.003)	-0.005** (0.003)	-0.013*** (0.005)	-0.007 (0.005)	-0.007*** (0.003)	-0.003 (0.002)
Output Tariff * (Income Group) ₁₉₉₈	0.012 (0.013)	0.009 (0.013)	0.012** (0.006)	0.011* (0.006)	0.017* (0.009)	0.008 (0.009)	0.010* (0.006)	0.006 (0.006)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Income Group-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province-Year FE		Y		Y		Y		Y
Adjust-R Square	0.73	0.75	0.73	0.74	0.81	0.82	0.81	0.82
Obs.	15177	15171	15177	15171	15392	15387	15392	15387
Number of Counties	1905	1905	1905	1905	1907	1907	1907	1907

Notes: This table estimates the effect of input and output tariffs on county-level emissions with respect to the initial nighttime light density in 1998, which performs as a proxy for per capita GDP. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. The variable (Income Group)₁₉₉₈ is a dummy variable, which equals to 1 if county's light density is higher than the median level in 1998, = 0 otherwise. Both independent variables (input tariff and output tariff) are lagged for one year. Standard errors in parentheses are clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Effects of Trade Openness on Economy w.r.t Initial Economy Status

	ln(Light Density)		ln(Number of Lights)		ln(per capita Lights)	
Panel A. OLS Estimation						
	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff	-0.009*** (0.003)	-0.009*** (0.003)	-0.012*** (0.004)	-0.012*** (0.004)	-0.010*** (0.004)	-0.011*** (0.004)
Input Tariff * (Income Group) ₁₉₉₈	0.003 (0.004)	0.000 (0.004)	0.006 (0.005)	0.003 (0.005)	0.004 (0.006)	0.002 (0.006)
Output Tariff	-0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
Output Tariff * (Income Group) ₁₉₉₈	0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.000 (0.002)	0.000 (0.002)
County FE	Y	Y	Y	Y	Y	Y
Income Group-Year FE	Y	Y	Y	Y	Y	Y
Province-Year FE		Y		Y		Y
Adjust-R Square	0.99	0.99	0.96	0.97	0.94	0.95
Obs.	26280	26279	26280	26279	18869	18869
Number of Counties	2753	2753	2753	2753	1978	1978
Panel B. IV Esimation						
	(1)	(2)	(3)	(4)	(5)	(6)
Input Tariff	-0.009** (0.004)	-0.009** (0.003)	-0.012*** (0.004)	-0.011*** (0.004)	-0.010** (0.004)	-0.011*** (0.004)
Input Tariff * (Income Group) ₁₉₉₈	0.004 (0.005)	0.001 (0.004)	0.006 (0.005)	0.003 (0.005)	0.002 (0.007)	0.002 (0.006)
Output Tariff	-0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.002 (0.001)
Output Tariff * (Income Group) ₁₉₉₈	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.002)	0.000 (0.002)
County FE	Y	Y	Y	Y	Y	Y
Income Group-Year FE	Y	Y	Y	Y	Y	Y
Province-Year FE		Y		Y		Y
Adjust-R Square	0.99	0.99	0.96	0.97	0.94	0.95
Obs.	26280	26279	26280	26279	18869	18869
Number of Counties	2753	2753	2753	2753	1978	1978

Notes: This table estimates the effect of input and output tariffs on county-level lights with respect to the initial light density in 1998, which performs as a proxy for per capita GDP. Both results from OLS and IV estimations are provided. The instrument from 2001 onward is the maximum allowable tariff under the WTO agreement. The variable (Income Group)₁₉₉₈ is a dummy variable, which equals to 1 if county's light density is higher than the median level in 1998, = 0 otherwise. Both independent variables (input tariff and output tariff) are lagged for one year. Standard errors in parentheses are clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A Data Appendix: Nighttime Light Data Process

A.1 Data Process

We first obtain annual nighttime light density at each grid of $0.01 \text{ degree} \times 0.01 \text{ degree}$ (around $1\text{km} \times 1\text{km}$) from the process discussed in [Section 4](#), then union it with the China's county map. [Figure A.4](#) shows how we calculate each county's nighttime light density: Different gridded colors represent different light density, and A is the area of the whole county. The gridded light density map can divide the county A into four subarea from A_1 to A_4 . Then we use the area of each subarea as a weight to calculate the light density in the whole county.

The math process presents in [Eq.11](#), where x_1 , x_2 , y_1 , and y_2 refer to the light density in each grid. The area of the county is divided by grid to four subareas, A_1 to A_4 . $\sum A$ indexes the county's area or the sum of all subareas.

$$PM_{2.5} = \frac{x_1 A_1 + x_2 A_2 + x_3 A_3 + x_4 A_4}{\sum A} \quad (11)$$

A.2 Cross-Validation

We perform several cross-validation exercises investigating the relationship between luminosity and various economic indicators across counties in China during my research period 1998-2008.

We start by examining whether luminosity correlates with development across counties. [Figure A.5](#) illustrates the unconditional correlation between log light density and log GDP per capita in four years. From 1998 to 2008, the R^2 ranges from 0.35 to 0.47, which is similar to the results of [Michalopoulos and Papaioannou \(2013\)](#). [Table A.1](#) reports the separate cross-sectional regressions over study periods. In panel A and B, I control the province and city fixed effect, respectively. In column (1) to (3) of [Table A.2](#), I report the results on panel regression. Both results suggest a robust correlation between the luminosity density and per capita GDP, where the coefficient is around 0.5. Column (4) and (5)

report the results when I regress the changes in per capita GDP on changes in light density between 2008 and 1998. It also suggests a strong correlation between the growth rates of GDP and light density.

To validate the correlation between the GDP and number of lights, [Table A.3](#) similarly reports the regression results on GDP and number of lights. I apply the same strategy to regress the changes in both measurements in column (4) and (5). Both results also suggest a stronger correlation between GDP and number of lights, where R^2 and coefficient increase and the significance remains at 99% confidence level. The cross-validation results imply it is doable to apply the luminosity data as a proxy for economics statistics across China's counties.

Figure A.1: Evolution of Imports in China: Share of Imports

Notes: The solid blue line and dashed green line represent the trade volumes shares on intermediates and final goods in China from 1994 to 2016, respectively. The vertical red line indicates the year 2001 when China joined WTO. Data Source: National Bureau of Statistics (NBS) of China.

Figure A.2: Evolution of Industrial Level Import Tariff Reductions on Inputs and Outputs

Notes: The solid lines show the median industrial-level weighted average input and output tariffs, the shaded area (for output tariffs) and dashed lines (for input tariffs) show the interquartile range.

Figure A.3: County-level Tariff in 1998 and 2007

Input Tariff in 1998

(a) Input Tariff 1998

Output Tariff in 1998

(b) Output Tariff 1998

Input Tariff in 2007

(c) Input Tariff 2007

Output Tariff in 2007

(d) Output Tariff 2007

Figure A.4: Process of the County-level Nighttime Light Density Calculation

Figure A.5: Luminosity and per capita GDP across China's Counties

Notes: The x-axis represents the logarithm of light density, y-axis refers to the logarithm of per capita GDP (RMB Yuan).

Figure A.6: Luminosity and GDP across China's Counties

Notes: The x-axis represents the logarithm of number of lights, y-axis refers to the logarithm of GDP (Million RMB Yuan).

Table A.1: Luminosity and per capita GDP across China's Counties

	per capita GDP (Yuan, log)										
	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Panel A: Control for Province Fixed Effect											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ln(Light Density)	0.536*** (0.029)	0.553*** (0.023)	0.501*** (0.023)	0.522*** (0.024)	0.511*** (0.021)	0.594*** (0.025)	0.587*** (0.024)	0.580*** (0.024)	0.569*** (0.024)	0.564*** (0.025)	0.492*** (0.024)
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjust-R Square	0.55	0.56	0.55	0.56	0.57	0.59	0.59	0.56	0.55	0.53	0.50
Obs.	1889	1890	1890	1890	1889	1889	1890	1891	1891	1890	1842
Panel B: Control for City Fixed Effect											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ln(Light Density)	0.532*** (0.026)	0.544*** (0.027)	0.495*** (0.023)	0.516*** (0.024)	0.496*** (0.023)	0.558*** (0.027)	0.549*** (0.026)	0.568*** (0.025)	0.578*** (0.027)	0.585*** (0.029)	0.546*** (0.027)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjust-R Square	0.76	0.76	0.77	0.77	0.78	0.78	0.77	0.76	0.76	0.75	0.74
Obs.	1864	1865	1865	1865	1864	1864	1866	1867	1867	1866	1817

Notes: This table cross-sectionally estimates the relationship between the county-level per capita GDP and nighttime light density from 1998 to 2008.

Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Luminosity and per capita GDP across China's Counties

	per capita GDP (Yuan, log)				
	All Years			$\Delta_{2008-1998}$	
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{Light Density})$	0.544*** (0.022)	0.528*** (0.021)	0.318*** (0.026)		
$\Delta_{2008-1998} \ln(\text{Light Density})$				0.120*** (0.011)	0.113*** (0.014)
County FE			Y		
City FE		Y			Y
Province FE	Y			Y	
Year FE	Y	Y	Y		
Adjust-R Square	0.66	0.82	0.94	0.40	0.60
Obs.	20742	20742	20742	1832	1807
Number of Counties	1893	1893	1893	1832	1807

Notes: This table estimates the relationship between the county-level per capita GDP and nighttime light density from 1998 to 2008. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Luminosity and GDP across China's Counties

	GDP (Million Yuan, log)				
	All Years			$\Delta_{2008-1998}$	
	(1)	(2)	(3)	(4)	(5)
ln(Number of Lights)	0.7274*** (0.0127)	0.6707*** (0.0125)	0.1180*** (0.0112)		
$\Delta_{2008-1998}$ ln(Number of Lights)				0.0001413*** (0.000)	0.0001427*** (0.000)
County FE			Y		
City FE		Y			Y
Province FE	Y			Y	
Year FE	Y	Y	Y		
Adjust-R Square	0.81	0.88	0.97	0.49	0.64
Obs.	20731	20731	20731	1831	1806
Number of Counties	1892	1892	1892	1831	1806

Notes: This table estimates the relationship between the county-level per GDP and nighttime light density from 1998 to 2008. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Number of Lights and Industrial Outputs across China's Counties

	Industrial Output (Million Yuan, log)											All Years	
	1998 (1)	1999 (2)	2000 (3)	2001 (4)	2002 (5)	2003 (6)	2004 (7)	2005 (8)	2006 (9)	2007 (10)		(11)	(12)
ln(Number of Lights)	1.046*** (0.043)	1.027*** (0.044)	0.933*** (0.035)	0.976*** (0.040)	0.949*** (0.041)	1.039*** (0.039)	1.073*** (0.041)	1.032*** (0.034)	1.011*** (0.035)	0.992*** (0.035)		0.977*** (0.029)	0.233*** (0.031)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	
Year FE												Y	Y
County FE													Y
Adjust-R Square	0.65	0.63	0.66	0.69	0.68	0.70	0.71	0.71	0.71	0.71		0.72	0.91
Obs.	2421	2515	2566	2489	2496	2523	2572	2608	2607	2618		25549	25547
Number of Counties	2421	2515	2566	2489	2496	2523	2572	2608	2607	2618		2663	2661

Notes: This table estimates the relationship between the county-level industrial output and number of lights. Columns (1) to (10) report the results from the cross-sectional regressions for each year. Columns (11) and (12) present the panel regression results for the whole period. Standard errors in parentheses are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.