Trade Uncertainty and Firm Pollution: The Role of Emission Cap

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Abstract

How does a reduction in trade policy uncertainty affect firms' pollution behavior? Guided by a simple model, we show that the answer to this question depends on whether an emission cap exists. We find that the reduced uncertainty increases firm output by comparable magnitudes across the regions, but they reduce firm SO2 emission intensity and firm total SO2 emissions only in regions with emission caps. The decline in SO2 emissions is caused by reduced use of fossil fuel and more abatement equipment. We also find that the reduced uncertainty improves firms' productivity when emission caps exist.

Keywords: Trade policy uncertainty, environmental regulation, emission cap, firm pollution, firm productivity

JEL codes: F18, F64, Q56, Q58

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1 Introduction

Globalization in recent decades has drastically transformed the economic and environmental landscapes of the world. Faced with a dilemma about economic prosperity and clean environment, developing countries may intentionally choose weaker environmental regulations to gain more from globalization, which may also become a source of comparative advantage (Levinson and Taylor, 2008; Hanna, 2010; Broner et al., 2012; Aichele and Felbermayr, 2015). This institutional inefficacy has all too often been credited as the reason for the deteriorating environment in developing countries (Banerjee et al., 2008; Alpert et al., 2012; Greenstone and Hanna, 2014). Is it possible that economic growth is obtained without sacrificing the environment? In particular, when a stringent environmental regulation is adopted, will a country fail to capture the gains from trade opportunities? We address these two questions in this study.

In October 2000, the U.S. government granted permanent normal trade relations (PNTR) to China, which became effective upon China's accession to the WTO at the end of 2001. Prior to the conferral of PNTR, although Chinese exports to the US had been subject to low tariffs, these tariffs were reviewed by the U.S. congress annually, which adds uncertainty to the tariffs faced by Chinese exporters. The conferral of PNTR ended trade policy uncertainty (Pierce and Schott, 2016). Recent studies find that the end of trade uncertainty had substantial effects on exports from China to the U.S. as well as internal migration in China (Pierce and Schott, 2016; Handley and Limao, 2017; Facchini et al., 2019).

We use the reduction in trade policy uncertainty as an exogenous positive shock to Chinese firms' export opportunities. How will the export shock impact Chinese firms' pollution behavior? On the one hand, the reduction in uncertainty incentivizes exports and production, which increases pollution (a *scale* effect). On the other hand, the larger production scale and higher profits may encourage firms to adopt better and possibly cleaner machines and technology to improve energy efficiency, which reduces pollution intensity, measured as pollution per unit of output (a *technology* effect). This technology effect that reduces pollution is also documented in the literature (Levinson and Taylor, 2008; Broner et al., 2012; Cherniwchan, 2017). What the literature has not yet examined are the differential effects of trade on firm pollution with different extents of emission control, modeled in our setting as emission caps faced by firms.

To more thoroughly analyze the effects of trade policy uncertainty reduction on firm pollution, under the condition that firms face emission control, we develop a multi-country model with heterogeneous firms, where firms' production entails environmental emissions. In our model, firms make export decisions to maximize profits and face government emission control policies as a production constraint. Our model predicts that when firms face an emission cap, reductions in trade policy uncertainty induce firms to produce more output but emit less pollution. Reductions in uncertainty also induce firms to use more labor to substitute for fossil fuel and invest more in abatement equipment. In contrast, when firms face no emission control, although uncertainty reduction increases firm production, it no longer reduces firm pollution.

We test the model predictions using data from three sources. The first dataset is the Annual Survey of Industrial Firms (ASIF), which contains information on firm production, such as output, employment, capital, and intermediate inputs. Second, we use data from the Annual Environmental Survey of Polluting Firms (AESPF), which covers major pollutants at the plant level. It also includes information on firm abatement equipment investment. We focus on variables related to sulfur dioxide (SO2) emissions because the emission cap in China mainly imposes constraints on firm SO2 emissions. The third dataset is transaction-level import and export data from the China General Administration of Customs (CGAC).

Following Erten and Leight (2019) and Facchini et al. (2019), we compute trade policy uncertainty at the prefecture level. As the conferral of PNTR eliminates export policy uncertainty from China to the U.S., firms in prefectures with higher levels of average uncertainty prior to the conferral would experience a greater decline in prefecture average uncertainty. We use a difference-in-differences (DID) estimator that compares firm output and SO2 emissions in high- and low-uncertainty prefectures before and after the conferral. We find that the reduction in uncertainty significantly increased firm production but reduced SO2 emissions per unit of output (SO2 intensity). We conduct event studies on firm output and SO2 intensity to justify our identification assumption for our DID estimator. The parallel trends show that the effect on output and SO2 intensity starts in 2001. Firms in prefectures with high and low trade policy uncertainty would have followed the same trends in production and SO2 emissions in the absence of PNTR conferral.

We then explore the heterogeneous effects across regions with different degree of environmental regulations. In 1998, two-control zones (TCZs) were established by the Chinese government as special regions with more stringent SO2 emission regulations. We present the geographic locations of the TCZs in Figure 1. The SO2 emission cap is more strictly enforced in TCZs than in non-TCZs. The spatial variation in SO2 emissions control allows us to examine the heterogeneous effects of uncertainty reductions in firm production and SO2 emissions in TCZs and non-TCZs. Consistent with our prediction, we find that the reductions in trade policy uncertainty increase firm output in both TCZs and non-TCZs by comparable magnitudes, but they reduce total firm emissions and emission intensity only in TCZs.

What explains the effects of reduced uncertainty on emission intensity for firms in TCZs? We find that the reduction in uncertainty decreases coal and fuel use, increases manual labor, and increases investment in abatement equipment for firms in TCZs. In contrast, we do not find comparable effects for firms in non-TCZs. In addition, we find that firms in TCZs improve total factor productivity more as a result of the reduced uncertainty, consistent with the Porter hypothesis which states that a tougher environmental standard can make firms more efficient and innovative (Porter and Van der Linde, 1995).[1]

Our study is related to two strands of literature. First, this paper is closely related to the emerging literature that uses firm- or plant-level data to examine the impact of trade on the environment. The current literature primarily focuses on developed countries–in particular the U.S.–to document that exporters pollute less than non-exporters (Holladay, 2016; Cui et al., 2016; Forslid et al., 2018). Cherniwchan (2017) further analyzes the impact of trade liberalization on a firm's total emissions and emission intensity in the context of NAFTA. In a developing country context, Barrows and Ollivier (2016) use Indian firm-level data to study the effects of an export demand shock on total emissions, output, and emission intensity. Gutierrez and Teshima (2018) use Mexican plant-level and satellite imagery data to examine the impact of import competition generated by output tariff reductions on plants' environmental outcomes. Our paper complements these earlier studies by focusing on the impact of an export demand shock induced by reduced trade policy uncertainty on Chinese firms' total emissions, output and emission intensity. Moreover, we examine the differences in these effects across regions with different degrees of environmental regulations on pollution emissions. To summarize, our paper is in line with the literature but also differs from it by emphasizing the role of the emission control.

Second, our paper is also related to studies on trade policy uncertainty. Pierce and Schott (2016) study the effect of a reduction in U.S. trade policy uncertainty on U.S. manufacturing firms after China's accession to the WTO. Handley and Limao (2017) use a dynamic general equilibrium model to argue that a reduction in trade policy uncertainty after China's accession to the WTO significantly contributed to the country's export boom to the United States. Crowley et al. (2018), Garred (2018), and Imbruno (2019) provide em-

[1] Our findings highlight the joint effects of export opportunity and domestic environmental regulation. When firms face an opportunity to export, and existing domestic environmental regulations constrain pollution, firms may adjust production and improve efficiency to increase production scale and export. This is consistent with the Porter hypothesis (Porter and Van der Linde, 1995). The positive effects of more stringent environmental regulations on firm productivity are also documented by Acemoglu et al. (2016), Aghion et al. (2016), Gutierrez and Teshima (2018), and Aghion et al. (2020).

pirical evidence on how trade policy uncertainty affects exports and imports. Erten and Leight (2019) and Facchini et al. (2019) examine the impacts of the reduction in trade policy uncertainty associated with China's WTO accession on structural transformation in China and China's "Great Migration", respectively. The focus of our paper is the environmental consequences of trade policy uncertainty, which differs from the aforementioned studies.

The remainder of the paper proceeds as follows. Section 2 introduces environmental regulations and TCZs in China. Section 3 presents a simple model. Section 4 discusses our empirical strategy and describes the data and measures. Section 5 reports the empirical results. Section 6 concludes the paper.

2 Institutional Background

The traditional method to control industrial pollution in China requires firms' pollution discharge to be below a given concentration value, which specifies the maximum level of emission intensity (i.e., emissions per unit of output) for each pollutant. Failure to comply with the requirement may trigger fines and penalties. This method, however, ignores the total amount of pollution of a firm, which leaves a loophole that results in high levels of overall pollution at the firm and regional levels. To close this loophole, China adopted an emission cap method in 1996 as a part of the 9th Five-year Plan. This method sets an overall emission target for all major pollutants and has since been the main method for pollution control in China.[2]

Emission caps are common practice across countries. For example, the U.S. created the "Acid Rain Program" and Japan initiated the "Water-basin COD Emission Target Control Program" to combat chemical emissions; there is also of course the worldwide carbon emission reduction agreement under the Kyoto Protocol.[3] In contrast to the common cap-and-trade mechanism, the method in China sets an overall cap but has no trading mechanism, primarily because China has not yet established institutions to support market transactions of emission permits.

In practice, the central government first sets a national cap, or emission target and then allocates targets to each province, and each province then divides the targets among pre-

[2] The 9th Five-year Plan defined 12 pollutants as "critical pollutants" and requires the total emissions of each pollutant in 2000 to be lower than those in 1995. The 10th Five-year Plan further mandated that the emissions of 6 major pollutants be reduced by 10% in 2005 relative to 2000 (see the "National Environmental Bureau, Decomposition Plan on Emission Control of Critical Pollutants during the 10th Five-year Plan, 2001").

[3] See the United Nations Framework Convention on Climate Change.

fectures in its jurisdiction for implementation. There are 333 prefectures in total, which form a government hierarchy in between provinces and counties.[4] The target assignments at the prefecture level take into account the population, economic size, industrial structure, past emissions, and environmental quality of each prefecture.[5] Each prefecture then further assigns emission targets to firms; the detailed assignment rules are not made public by the government. Guaranteeing emission reductions demands not only careful scrutiny and government approval at the factory or establishment level, especially in high-pollution industries, but also requirements by the prefecture government that firms adopt pollution abatement facilities such as desulfurization of coal or gas combustion or to remove sources with high emission intensity and outdated production equipment. The government regularly sends inspectors to monitor and record pollution emissions to enforce its regulation.

In effect, this emission cap method is applied nationwide and implemented through the government administrative hierarchy. The amounts of pollution emissions are recorded at the firm level before they are summed up at jurisdictional levels. Statistics are reported through government hierarchies in a bottom-up manner and affirmed by the central government. The central government uses these statistics to evaluate officials' competency and accountability. This process takes place annually.

Among all pollutants that are regulated by an emission cap in China, SO2 is granted the top priority. In January 1998, the central government enacted a "Two-control Zone" policy to identify priority regions to reduce SO2 emissions to prevent acid rain. Prefectures with annual average precipitation pH values exceeding nationally mandated thresholds are designated as Acid Rain Control Zones: prefectures with annual average SO2 emission levels exceeding nationally mandated thresholds are designated as SO2 Control Zones. Following these standards, a total of 175 prefectures were designated as "Two-control Zones" (TCZs) by the central government in 1998. More stringent environmental regulations on emission caps are thus adopted in these zones. For example, new coal mines producing coal with sulfur content higher than 3% are prohibited, and any such existing coal mines are to be shut down. No new thermal power plants combusting coal are to be built near large prefectures. Firms in high-emission-intensity industries including the petrochemical, metallurgical, architecture material, and nonferrous metal industries are obliged to adopt pollution reduction equipment.[6] These requirements are more

[4]The 333 prefecture-level divisions include 7 prefectures, 293 prefecture-level cities, 30 autonomous prefectures, and 3 leagues. We call all of these types of divisions prefectures for simplicity.

[5]See the "National Environmental Bureau, Implementing Program on Emission Control of Critical Pollutants during the 9th Five-year Plan, 1997."

[6]See the "Approval of The Central Government on SO2 Control Zones and Acid Control Zones Plan,

stringent in TCZs than those in non-TCZs.

Figure 2 plots the annual aggregate GDP and SO2 emissions in TCZs and non-TCZs between 1999 and 2006. The GDP data are obtained from the CEIC database, and the SO2 emission data are collected from the China Statistical Yearbook on Environment, published by the Ministry of Ecology and Environment of China. We treat 1999 as the benchmark year (value=100). The figure shows that although GDP had been rising rapidly in both types of region, the SO2 emissions in TCZs remained relatively stagnant between 1999 and 2006, which reveals the relatively more stringent SO2 emission control in TCZs. The difference in the strength of environmental regulation between TCZs and non-TCZs helps us to identify the differential impacts of reduced trade policy uncertainty on firm behavior with and without an emission cap.

3 Model

In this section, we develop a multi-country trade model with heterogeneous firms where firms' production entails environmental emissions.

3.1 Preferences

A representative consumer in country j has a constant elasticity of substitution (CES) utility function given by:

$$U_j = \left[\sum_{i=1}^{N} \int_{\omega \in \Omega_{ij}} \left[q_{ij} (\omega) \right]^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} + \Psi \left(E_j \right), \tag{1}$$

where N represents the total number of countries and i is the source country of the product, ω indexes the product variety in set Ω_{ij} available in country j, q_{ij} denotes the quantity of variety ω, $\sigma > 1$ is the elasticity of substitution between varieties, and $\Psi \left(E_j \right) < 0$ represents the negative impact of pollution emission E_j on the individual's utility.[7] Consumer optimization yields the following the demand function for variety ω in country j:

$$q_{ij} (\omega) = \left[p_{ij} (\omega) \right]^{-\sigma} P_j^{\sigma-1} I_j, \tag{2}$$

1998."

[7] We assume that $\Psi \left(E_j \right) < 0$ and $\Psi' \left(E_j \right) < 0$. That is to say, the impact of pollution emission on individual's utility is negative and this negative impact increases in pollution emission E_j.

where $p_{ij}(\omega)$ is the price of variety ω faced by consumers in country j. The aggregate price index in country j is defined by $P_j = \left[\sum_{i=1}^{N} \int_{\omega \in \Omega_{ij}} p_{ij}(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$ and I_j is the total spending in country j.

3.2 Firm behavior

Suppose the firm is in the market of monopolistic competition. Each firm in country i produces only one kind of heterogeneous product and its productivity is φ. Like Melitz (2003), firms in country i need to pay f_i^e units of labor in order to acquire a blueprint and then draw a productivity from a Pareto distribution, i.e., $G_i(\varphi) = 1 - \left(\frac{b_i}{\varphi}\right)^{\theta}$, where θ is the Pareto location parameter and b_i represents the productivity of country i. Firms in country i need to pay a fixed export cost, amounting to f_{ij} units of domestic labor when exporting to country j. In addition, firms in country i also need to pay a tariff of t_{ij} when exporting to country j. To characterize trade policy uncertainty faced by Chinese firms exporting to the U.S. prior to PNTR conferral, we assume that the tariff can be set either at a high non-PNTR value at t_{ij}^1 with probability η_{ij} or at a low PNTR value at t_{ij}^2 with probability $1 - \eta_{ij}$. The average tariff is therefore $t_{ij} = \eta_{ij} t_{ij}^1 + (1 - \eta_{ij}) t_{ij}^2$, where $0 \leq \eta_{ij} \leq 1$.

Consider country i to be China. When $j =$ U.S., η_{ij} is above 0 prior to conferral, and it is equal to 0 after conferral. When $j \neq$ U.S., we assume that η_{ij} remains zero throughout the study period. In what follows, we analyze how the tariff change induced by the change in the probability η_{ij} affects the firm's production and emission behavior.

Following Shapiro and Walker (2018), we assume that each firm produces two outputs: an industrial good and emissions. In order to reduce emissions, a fraction of θ ratio of production inputs is used to reduce pollution and the other $(1-\theta)$ ratio of production inputs is used to produce products. The fraction of labor θ spent in reducing pollution is an endogenous choice that ultimately varies with a firm's productivity. The firm's production function is given by the following equation:

$$q_{ij}(\varphi) = (1-\theta)\varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i}, \tag{3}$$

where l_{ij} is the labor demand, M_{ij} is the demand for final material inputs by firms (its production function is the same as utility function). Firms product emissions with the following technology:

$$e_{ij}(\varphi) = (1-\theta)^{1/\alpha} \varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i}, \tag{4}$$

The firms need to pay the costs including the emission tax, pollution fee and so on. We assume that the pollutant cost per unit of emission is $t_{e,i}$.

We proceed by using Equation (3) to solve for $(1-\theta)$, and, in turn, be used to substitute for $(1-\theta)$ in Equation (4). This gives us an integrated expression for the joint production of goods and emission, which exploits the fact that although pollution is an output, it can equivalently also be treated as an input. Hence, we have:

$$q_{ij} = \left(\varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i}\right)^{1-\alpha} e_{ij}^{\alpha}. \tag{5}$$

In equation (5), production use labor as well as emissions. The parameter α denotes how intensive the industry is in the use of labor versus the use of emissions.

3.3 Firm's behavior

In the first stage, given the wage w_i, the pollutant cost per unit of emission $t_{e,i}$ and the export decision I_{ij}, firms solve the following problem:

$$\max \sum_j I_{ij}(\varphi) \left[\frac{p_{ij}(\varphi) q_{ij}(\varphi)}{\tau_{ij}} - w_i l_{ij}(\varphi) - P_i M_{ij} - t_{e,i} e_{ij}(\varphi)\right] \tag{6}$$

$$\text{where } q_{ij}(\varphi) = \left[p_{ij}(\varphi)\right]^{-\sigma} P_j^{\sigma-1} X_j^D \tag{7}$$

$$q_{ij}(\varphi) = (1-\theta_{ij}) \varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i} \tag{8}$$

$$e_{ij}(\varphi) = (1-\theta_{ij})^{1/\alpha} \varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i} \tag{9}$$

where X_j^D is the demand by both consumers and firms, $\frac{p_{ij}(\varphi)}{\tau_{ij}}$ denotes the value obtained by firms for one unit of export to country j and $\tau_{ij} = 1 + t_{ij}$. The previous problem is equivalent to

$$\max_{\theta_{ij}, l_{ij}} \sum_j I_{ij}(\varphi) \left[\frac{\left(\left(1-\theta_{ij}\right) \varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}}{\tau_{ij}} P_j^{\frac{\sigma-1}{\sigma}} I_j^{\frac{1}{\sigma}} - w_i l_{ij}(\varphi) - P_i M_{ij} - t_{e,i} \left(1-\theta_{ij}\right)^{1/\alpha} \varphi l_{ij}^{\gamma_i} M_{ij}^{1-\gamma_i}\right] \tag{10}$$

Solving this optimization problem by choosing θ_{ij}, l_{ij} and M_{ij} yields,

$$\alpha\frac{\sigma-1}{\sigma}p_{ij}(\varphi)q_{ij}(\varphi)=\tau_{ij}t_{e,i}e_{ij}(\varphi) \tag{11}$$

$$\gamma_i\frac{\sigma-1}{\sigma}p_{ij}(\varphi)q_{ij}(\varphi)=\tau_{ij}\left[w_i l_{ij}(\varphi)+\gamma_i t_{e,i}e_{ij}(\varphi)\right] \tag{12}$$

$$\left(1-\gamma_i\right)\frac{\sigma-1}{\sigma}p_{ij}(\varphi)q_{ij}(\varphi)=\tau_{ij}\left[P_i M_{ij}+\left(1-\gamma_i\right)t_{e,i}e_{ij}(\varphi)\right] \tag{13}$$

The previous equations imply the optimal price equal to

$$p_{ij}(\varphi)=\frac{\sigma}{\sigma-1}\frac{\tau_{ij}\left(w_i^{\gamma}P_i^{1-\gamma}\right)^{1-\alpha}t_{e,i}^{\alpha}}{\varphi^{1-\alpha}\alpha^{\alpha}\left(\left(1-\alpha\right)\gamma_i^{\gamma_i}\left(1-\gamma_i\right)^{1-\gamma_i}\right)^{1-\alpha}} \tag{14}$$

Firms decide on whether or not to sell in country j. The exporting productivity cutoff φ_{ij}^* is determined by comparing their profit and the fixed exporting cost according to the following equation:

$$\frac{1}{\sigma}\frac{p_{ij}(\varphi_{ij}^*)q_{ij}(\varphi_{ij}^*)}{\tau_{ij}}=f_{ij}w_i \tag{15}$$

Hence, the productivity cutoff φ_{ij}^* amounts to

$$\varphi_{ij}^*=\left(\frac{\sigma\tau_{ij}f_{ij}w_i}{\Theta_{ij}P_j^{\sigma-1}X_j^D}\right)^{\frac{1}{(1-\alpha)(\sigma-1)}} \tag{16}$$

where $\Theta_{ij}=\left(\frac{\sigma}{\sigma-1}\frac{\tau_{ij}\left(w_i^{\gamma}P_i^{1-\gamma}\right)^{1-\alpha}t_{e,i}^{\alpha}}{\alpha^{\alpha}\left(\left(1-\alpha\right)\gamma_i^{\gamma_i}\left(1-\gamma_i\right)^{1-\gamma_i}\right)^{1-\alpha}}\right)^{1-\sigma}$.

3.4 Equilibrium

The average productivity of exporting firm from country i to country j, $\widetilde{\varphi}_{ij}$, is defined as:

$$\widetilde{\varphi}_{ij}=\left[\int_{\varphi_{ij}^*}^{\infty}\left(\varphi_{ij}\right)^{(1-\alpha)(\sigma-1)}\frac{g\left(\varphi\right)}{1-G\left(\varphi_{ij}^*\right)}d\varphi\right]^{\frac{1}{(1-\alpha)(\sigma-1)}}=\left(\frac{\theta}{\theta-\left(1-\alpha\right)\left(\sigma-1\right)}\right)^{\frac{1}{(1-\alpha)(\sigma-1)}}\varphi_{ij}^* \tag{17}$$

Since the average productivity level $\widetilde{\varphi}_{ij}$ is completely determined by the productivity cutoff φ_{ij}^*, the average profit and revenue levels from country i to country j are also tied to the cutoff level φ_{ij}^*:

$$\pi_{ij}\left(\widetilde{\varphi}_{ij}\right)=\frac{(1-\alpha)(\sigma-1)}{\theta}\frac{r_{ij}\left(\widetilde{\varphi}_{ij}\right)}{\sigma}=\frac{(1-\alpha)(\sigma-1)}{\theta-(1-\alpha)(\sigma-1)}\frac{r_{ij}\left(\varphi_{ij}^*\right)}{\sigma} \tag{18}$$

In the equilibrium with free entry, the expected value for potential entrants should be equal to the fixed entry cost $f_i^e w_i$, i.e.,

$$N_i f_i^e w_i=\sum_j N_i\left(\frac{b}{\varphi_{ij}^*}\right)^{\theta}\pi_{ij}\left(\widetilde{\varphi}_{ij}\right)=\frac{(1-\alpha)(\sigma-1)}{\theta\sigma}Y_i \tag{19}$$

where Y_i denotes the total output:

$$Y_i=\sum\nolimits_j X_{ij} \tag{20}$$

where X_{ij} denoting the aggregate trade flow from country i to country j, equals to

$$X_{ij}=\frac{N_i\theta\sigma b^{\theta}\left(\tau_{ij}f_{ij}w_i\right)^{1-\frac{\theta}{(1-\alpha)(\sigma-1)}}\Theta_{ij}^{\frac{\theta}{(1-\alpha)(\sigma-1)}}\tau_{ij}^{-1}}{\sum_{i'}N_{i'}\theta\sigma b^{\theta}\left(\tau_{i'j}f_{i'j}w_{i'}\right)^{1-\frac{\theta}{(1-\alpha)(\sigma-1)}}\Theta_{i'j}^{\frac{\theta}{(1-\alpha)(\sigma-1)}}}X_j^D \tag{21}$$

where X_j^D is the sum of the consumers' demand I_j and the firms' demand $\frac{\left(1-\gamma_j\right)(1-\alpha)(\sigma-1)}{\sigma}Y_j$. Consumer's expenditure I_j satisfies:

$$I_j=w_jL_j+t_{e,j}E_j+\sum_i t_{ij}X_{ij} \tag{22}$$

The equation (12) implies that the total emission satisfies:

$$t_{e,i}E_i=\frac{\sigma-1}{\sigma}\alpha\sum\nolimits_j X_{ij}=\frac{\sigma-1}{\sigma}\alpha Y_i \tag{23}$$

Trade balance condition, which means that the total expenditure amounts to sell revenue plus tariff revenue, implies:

$$w_iL_i=\left(1-\frac{\left(\left(1-\gamma_i\right)(1-\alpha)+\alpha\right)(\sigma-1)}{\sigma}\right)Y_i \tag{24}$$

Aggregate price could be rewritten as

$$P_j = \left[\sum_i N_i \left(\frac{b}{\varphi_{ij}^*}\right)^{\theta} \int_{\varphi_{ij}^*}^{\infty} p_{ij}(\varphi)^{1-\sigma} \frac{g(\varphi)}{1-G\left(\varphi_{ij}^*\right)} d\varphi\right]^{\frac{1}{1-\sigma}} \tag{25}$$

$$= \left[\sum_i \frac{N_i b^{\theta}\theta}{\theta-(1-\alpha)(\sigma-1)} \left(\frac{\sigma\tau_{ij} f_{ij} w_i}{\Theta_{ij} X_j^D}\right)^{-\frac{\theta}{(1-\alpha)(\sigma-1)}} \frac{\sigma\tau_{ij} f_{ij} w_i}{X_j^D}\right]^{-\frac{1-\alpha}{\theta}} \tag{26}$$

Using a method inspired by Dekle, Eaton, and Kortum (2007; 2008), we denote the post adjustment value of any variable x as x' and the change in its value as $\widehat{x} = \frac{x'}{x}$, a hat denotes the ratio between the counterfactual and factual value. The emission control system, together with Equations (19), (20), (22), (23), (24) and (26), construct the equilibrium system with variables (w_i, E_i, $t_{e,i}$, P_i Y_i, I_i, N_i). These four equations imply:

$$\widehat{Y}_i = \sum_j \lambda_{ij} M_{ij} \tag{27}$$

$$\widehat{I}_j = \frac{w_j L_j}{I_j}\widehat{w}_j \widehat{L}_j + \frac{t_{e,j}E_j}{I_j}\widehat{t}_{e,j}\widehat{E}_j + \sum_i \frac{t_{ij}X_{ij}}{I_j} M_{ij} \tag{28}$$

$$\widehat{Y}_i = \widehat{w}_i \widehat{N}_i \tag{29}$$

$$\widehat{Y}_i = \widehat{t}_{e,i}\widehat{E}_i \tag{30}$$

$$\widehat{Y}_i = \widehat{w}_i \tag{31}$$

$$\widehat{P}_j = \left[\sum_i \xi_{ij}\widehat{N}_i \left(\widehat{\tau}_{ij}\widehat{w}_i^{\gamma(1-\alpha)}\widehat{P}_i^{(1-\gamma)(1-\alpha)}\widehat{t}_{e,i}^{\alpha}\right)^{-\frac{\theta}{1-\alpha}} \left(\frac{\widehat{\tau}_{ij}\widehat{w}_i}{\widehat{X}_j^D}\right)^{1-\frac{\theta}{(1-\alpha)(\sigma-1)}}\right]^{-\frac{(1-\alpha)}{\theta}} \tag{32}$$

where $M_{ij} = \frac{\widehat{N}_i\left(\widehat{\tau}_{ij}\widehat{w}_i\right)^{1-\frac{\theta}{(1-\alpha)(\sigma-1)}}\left(\widehat{\tau}_{ij}\widehat{w}_i^{\gamma(1-\alpha)}\widehat{P}_i^{(1-\gamma)(1-\alpha)}\widehat{t}_{e,i}^{\alpha}\right)^{-\frac{\theta}{1-\alpha}}\widehat{\tau}_{ij}^{-1}}{\sum_{i'}\widehat{N}_{i'}\xi_{i'j}\left(\widehat{\tau}_{i'j}\widehat{w}_{i'}\right)^{1-\frac{\theta}{(1-\alpha)(\sigma-1)}}\left(\widehat{\tau}_{i'j}\widehat{w}_{i'}^{\gamma(1-\alpha)}\widehat{P}_{i'}^{(1-\gamma)(1-\alpha)}\widehat{t}_{e,i'}^{\alpha}\right)^{-\frac{\theta}{1-\alpha}}}\widehat{X}_j^D$, $\widehat{X}_j^D = \frac{I_j}{X_j^D}\widehat{I}_j + \frac{\left(1-\gamma_j\right)(1-\alpha)(\sigma-1)Y_j}{\sigma X_j^D}\widehat{Y}_j$, $\lambda_{ij} = \frac{X_{ij}}{\sum_j X_{ij}}$, $\xi_{ij} = \frac{\tau_{ij}X_{ij}}{\sum_i \tau_{ij}X_{ij}}$, $X_i^D = \sum_j X_{ij} + \sum_v t_{vi}X_{vi}$, $I_i = \left(1-\frac{(1-\gamma_i)(1-\alpha)(\sigma-1)}{\sigma}\right)\sum_j X_{ij} + \sum_v t_{vi}X_{vi}$, $Y_i = \sum_j X_{ij}$, $w_i L_i = \left(1-\frac{((1-\gamma_i)(1-\alpha)+\alpha)(\sigma-1)}{\sigma}\right)\sum_j X_{ij}$, $t_{e,i}E_i = \frac{\alpha(\sigma-1)}{\sigma}\sum_j X_{ij}$. Following Hsieh and Ossa (2016), we treat the mean change in all countries' wage index as the numeraire. Then, we can use the previous several equations to solve for the changes in variables at general equilibrium in response to a reduction in trade uncertainty, given bilateral trade data and values of the key parameters.

We assume that only China has adopted emission target control theme. As for country i except from China, pollution cost $\widehat{t}_{e,i}$ in that country is unrelated with trade activities since they wouldn't adopt emission target control theme. According to Equation (30), we have $\widehat{E}_i = \widehat{Y}_i$ for $i \neq China$. For China, we set $\widehat{E}_i = (1-\rho)\widehat{Y}_i + \rho\kappa$, where $0 \leq \rho \leq 1$ and $0 < \kappa \leq 1$. When $\rho = 0$, there is no emission controls in China. A higher value of ρ corresponds to more stringent emission control. The value of κ reflects the emission cap. For example, $\kappa = 0.975$ means the emission cap is the 97.5 percentage of its initial value.

3.5 Data, Parameters and Results

This section describes how we estimate the parameters in the quantitative analysis, then simulates the estimated effects of a reduction in trade uncertainty.

The elasticity of substitution σ, the pollution elasticity α and the trade elasticity θ are estimated pursuant to steps suggested by Shapiro and Walker (2018). To be specific, we take an overall value 0.011 for pollution elasticity α as Shapiro and Walker (2018), implying that firms pay 1.1 percent of their total production costs on pollution taxes. In accordance with Broda and Weinstein (2006) who estimate the product-specific elasticities of substitution for 73 counties based on a nested constant-elasticity-substitution utility function, we take the elasticity of substitution $\sigma = 5$.[8] According to our theory, firms' domestic sales follow a Pareto distribution with a shape parameter $\theta - (1-\alpha)(\sigma - 1)$. Given the estimates of σ and α, we could then back out the trade elasticity θ by regressing the logarithm of the rank of firm domestic sales on the logarithm of firm domestic sales, using Chinese firm-level manufacturing survey data from the National Bureau of Statistics of China (NBSC). The estimated value of θ equals to 4.41.

In order to solve for the equilibrium relative changes, we also need the complete matrix consisting of the trade flows X_{ij} and the tariff τ_{ij}. We first obtain the trade flows at year 2001 from World Input-Output Database (WIOD), covering 43 countries, and the rest of the world. Then, we obtain their bilateral applied tariff data at year 2001 from the WTO-TRAINS database. For U.S., its tariff imposed on imports from China is a function of non-MFN applied tariff and MFN applied tariff before China's accession to WTO. After China's accession to the WTO, it becomes the MFN applied tariff.

The first three panels of Figure 3 describes the impact of a reduction in policy uncertainty on output, emission and emission intensity, respectively. The last panel of Figure 3 reflects the impact of a reduction in policy uncertainty on $1-\theta$.[9] As shown in Figure 3, re-

[8]We aggregate their estimates for China and U.S. by taking means, which equal to 6.19 and 4.17 respectively. Hence, we take $\sigma = 5$, a value in-between.

[9]Figure 3 corresponds to the case of $\kappa = 0.975$. Figures A.1 and A.2 in the Appendix correspond to $\kappa = 1$ and $\kappa = 0.95$. We find similar patterns pertaining to the impact of diminished trade policy uncertainty among figures with different values of κ.

duction in trade policy uncertainty (i.e., higher probability of setting non-PNTR, η) raises output and pollution emission. When there exists the emission control (i.e., $\rho \neq 0$), the emission intensity decrease. As to output, diminished trade policy uncertainty increases output by 6%. More stringent environmental regulation only slightly weaken this output effect if the probability of setting non-PNTR before China's accession to WTO equals to one. After comparing two extreme situation when $\rho = 0$ and $\rho = 1$, we only find 0.13% less output impact from decreased trade policy uncertainty when incorporating the influence from strict environmental regulation. If the emission cap is lower than its initial benchmark value (i.e., $\kappa < 1$), the emission would turn from increase to decrease after a reduction in policy uncertainty. Trade policy uncertainty would not affect the emission intensity without emission control. It always equals to one. The emission cap reduces the emission intensity due to higher emission costs caused by more stringent environmental regulation (see Figure 4). Meanwhile, the last panel shows the substitutive relation of inputs between firms' production and emission control. Without emission control ($\rho = 0$), more inputs would be used in production which is indicated by the increase of $1 - \theta$. With stringent emission control ($\rho = 1$), more inputs are used in emission reduction which is indicated by the decrease of $1 - \theta$.

4 Empirical Specification, Data, and Measures

In this section, we specify our econometric models and describe the data and measures that we use for estimation.

4.1 Empirical specification

In this section, we present our empirical strategy to test our model predictions. Proposition 1 suggests that when an overall emission cap exists, reducing trade policy uncertainty increases firm production but reduces firm SO_2 emission intensity. We test this prediction by estimating the following regression:

$$y_{it} = \beta Uncertainty_p \times Post_t + \gamma X_{pt} + \sum_t \theta_t X_i \times \delta_t + \delta_t + \gamma_i + \epsilon_{it}, \tag{33}$$

where y_{it} denotes firm i's outcome in year t. $Uncertainty_p$ measures prefecture p's export policy uncertainty prior to WTO accession. Following Facchini et al. (2019), we use export-weighted uncertainty at the prefecture level to construct this variable. $Post_t$ is a dummy variable indicating whether year t is post WTO accession. We control for the interactions between year dummies and firm initial output and SO_2 emissions, X_i, to allow firms with different initial outputs and emissions to have different time paths. To alleviate biases caused by macroeconomic changes at the prefecture level, we also include the vector of controls X_{pt}, which includes contemporaneous prefecture-level GDP per capita and population density. δ_t and γ_i are year and firm fixed effects, respectively. Controlling for year fixed effects ensures that our estimates will not capture effects due to other concurrent macroeconomic changes or common time trends, and controlling for firm fixed effects eliminates any omitted variable bias caused by time-invariant firm characteristics. ϵ_{it} is an error term capturing all unobserved factors that influence y_{it}.

The main parameter of interest in equation (33) is β, which estimates how the change in a firm's outcome before and after WTO accession differs across firms in prefectures of different levels of pre-WTO export uncertainty. Our model predicts that, relative to firms located in prefectures with low uncertainty, firms in prefectures with high uncertainty prior to WTO accession increase output more. The overall emission control sets a constraint on total SO_2 emissions and therefore SO_2 emission intensity, i.e., per-unit output SO_2 emissions, is expected to decline. The effects on firm SO_2 emissions can be ambiguous.[10] To test these hypotheses, we use the logarithm of a firm's output, SO_2 emissions, or emission intensity of SO_2, as the dependent variable in equation (33). We expect β to be positive, zero (or negative), and negative, respectively, in these regressions.

To further test whether emission control is indeed the key driver of our results, we conduct a triple-difference estimation strategy to see if the policy effects are different for firms located in TCZs from those in non-TCZs. Firms in TCZs face more stringent SO2 emission control. The regression takes the following form:

$$\begin{aligned} y_{it} = {} & \beta_0 TCZ_i \times Uncertainty_p \times Post_t + \beta_1 Uncertainty_p \times Post_t + \beta_1 TCZ_i \times Post_t \\ & + \gamma X_{ct} + \sum_t \theta_t X_i \times \delta_t + \delta_t + \gamma_i + \epsilon_{it}, \end{aligned} \tag{34}$$

where TCZ_i is a dummy variable that indicates whether firm i is located in a two-control zone during our study period. We are interested in the estimated coefficient, β_0, which shows the heterogeneous policy effects by firm location. Because firms located in TCZs face more stringent emission control, we expect β_0 to be negative for firm SO_2 emissions and SO_2 emission intensity. For firm output, the expected sign of β_0 is ambiguous. On the one hand, there is a cost effect. Firms located in a TCZ face an emission cap that imposes

[10]The firm SO_2 emission cap may decline for two reasons. First, overall jurisdictional emissions are required to decline, especially for the TCZs. Second, if we allow firms to enter and exit, reduction in policy uncertainty increases firms' profits and induces more firm entry, which entails a larger number of firms. As a result, to keep overall emissions fixed, per-firm emission allowance should decline.

extra costs on firm production, and therefore, when trade policy uncertainty decreases, output increases should be smaller than those of firms located in non-TCZs. On the other hand, there is an efficiency effect. The emission cap may impel firms to adjust production inputs and improve efficiency (Porter hypothesis), which increases firm output. The sign of β_0 is determined by the relative importance of the two effects.

In addition, to study the mechanisms of these effects, we test whether firms use less fossil fuel but more alternative inputs to reduce emissions. We also examine the effects of reduced uncertainty on pollution abatement equipment. Finally, a reduction in uncertainty may also impel firms to improve production efficiency. Thus, we study the effects on firm productivity. All these exercises follow the specifications in equations (33) and (34).

4.2 Data source

To investigate the impact of trade uncertainty, we use the following three highly disaggregated firm-level datasets: (1) an annual firm-level manufacturing survey data from the National Bureau of Statistics of China (NBSC); (2) firm-level pollution emission data from the Annual Environmental Survey of Polluting Firms (AESPF); and (3) firm-product-level trade data from China's General Administration of Customs (CGAC).

First, we use the firm-level data from the Annual Survey of Industrial Firms (ASIF), which has been widely used in the literature on the Chinese economy (Brandt et al., 2009;Fan et al., 2015; Fan et al., 2018; Gan et al., 2016). This dataset contains rich firm-level information from 1998 to 2007, including basic firm information (e.g., firm name, address, age, ownership structure, employment, capital stock, gross output, and value added) and information on three major accounting statements (balance sheet, profit and loss account, and cash flow statement). We follow Fan et al. (2015) to clean the dataset.[11]

The second dataset on firms' pollution comes from the Annual Environmental Survey of Polluting Firms (AESPF) of China, which contains information on firms' environmental performance, including emissions of main pollutants (industrial effluent, waste air, COD, NH_3, NO_x, SO_2, smoke and dust, solid waste, noise, etc.), pollution abatement equipment, and energy consumption (usage of freshwater, recycled water, coal, fuel, clean gas, etc.), among others.[12] Due to a lack of consistent firm identifiers across different data

[11]We use the following standards to clean our dataset: (i) the total assets must be higher than the liquid assets; (ii) the total assets must be greater than the total fixed assets; (iii) the total assets must be greater than the net value of the fixed assets; (iv) a firm must have a unique identification number; and (v) the firm establishment time must be valid.

[12]Similar to the Annual Survey of Industrial Firms (ASIF), which provides the basis for the macroeconomic indicators, the AESPF contains the source data for calculating macro-level environmental indicators,

sets, we match the aforementioned data by firm name.

The third dataset is transaction-level import and export data from the China General Administration of Customs (CGAC). This dataset includes information on each import and export transaction of Chinese firms from 2000, including basic information about the firms (e.g., company name, telephone, zip code, contact person), firm type (e.g., state owned, domestic private, foreign invested, and joint ventures), and trade regime (e.g., "Ordinary", "Processing and Assembling" and "Processing with Imported Materials"). The first 4 digits of firm identification in customs data represent the prefecture identifiers, and thus we can use the customs data to calculate the import value by Chinese prefecture from the rest of world and the export value from each Chinese prefecture to the rest of world (in particular the U.S.) at the HS 6-digit level.

4.3 Measures

■ **Trade policy uncertainty**

We compute the trade policy uncertainty faced by Chinese exporters to the U.S. using the normal-trade-relations (NTR) gap measure developed by Feenstra et al. (2002). This measure is built to calculate the NTR tariffs applied by the U.S. on WTO members and the threatened tariffs (non-NTR tariffs) that would have been implemented had the most favored nation (MFN) status not been renewed to China by the U.S. Congress (Facchini et al., 2019). Following the literature, we use the NTR gap in 1999 at the HS6 level prior to the WTO accession that is widely used in recent studies (e.g., Handley and Limao, 2017, Erten and Leight, 2019, and Pierce and Schott, 2016). We then construct an export-weighted average of the NTR gap for each Chinese prefecture:

$$Uncertainty_p = \sum_{HS6} \frac{ExportUS_{HS6,p}}{\sum_{HS6} ExportUS_{HS6,p}} NTRgap_{HS6}, \tag{35}$$

where $NTRgap_{HS6}$ is the spread between the non-NTR tariff and NTR tariff at the Harmonized System (HS) 6-digit level in 1999. $ExportUS_{HS6,p}$ is the export value from Chinese prefecture p to the U.S. at the HS 6-digit level in 2000, which can be computed using data from the customs data. In the robustness check section, we use labor employment and exports to all countries as alternative weights to demonstrate the consistency of our results regardless of the weight choice. We also use the simple average NTR gap of all exports from prefecture p as an additional robustness check.

■ **Firm productivity**

such as the statistics reported in the China Statistical Yearbook on Environment.

To estimate the impact of trade uncertainty on firm productivity, we compute various measures of firm total factor productivity (TFP). Our primary TFP measure is revenue TFP using the method of Olley-Pakes (hereafter O-P) (Olley and Pakes, 1996). We run regressions of firm value-added against firm capital, which is computed using the perpetual inventory method, and firm employment.[13] Following Brandt et al. (2009), we deflate firms' capital and value added, using the input price deflators and output price deflators, respectively. As in Amiti and Konings (2007), we control for a firm's trade status in the TFP estimation by including two trade-status dummy variables—an export dummy (equal to 1 for exports and 0 otherwise) and an import dummy (equal to 1 for imports and 0 otherwise). We also control for a post-WTO dummy, which equals 1 if a year is after 2001 and 0 otherwise) in the O-P estimation because WTO accession represents a positive demand shock for China's exports. In addition to the O-P method, we also use the Ackerberg-Caves-Frazer augmented O-P methods (Ackerberg et al., 2015) to estimate TFP.

■ **Other covariates**

To isolate the impact of trade policy uncertainty, we also control for other concurrent policy changes as robustness checks. According to Erten and Leight (2019) and Facchini et al. (2019), major domestic reforms during China's accession to the WTO included reductions in import tariffs, the elimination of import licensing requirements, the elimination of textile and clothing import quotas and reduced restrictions on FDI. We use data on China's import tariffs from the WITS database, data on export licensing requirements from Bai et al. (2017), data export quota from Brambilla et al. (2010) and Handley and Limao (2017), and data on the nature of contracting from Nunn (2007) to control for these policy changes. We then aggregate the industry-level export licenses at the prefecture level. Prefecture average import tariff rates are weighted by import value, whereas all other variables are weighted by export value for each prefecture.

Specifically, for export licenses, we match the customs data with the ASIF dataset, in which firms reporting positive export values in both data sets in a specific year are classified as having an export license. Firms reporting positive export values only in the ASIF data set are defined as indirect exporters.[14] We calculate the ratio of direct exporters in a given industry to measure the extent to which an industry was affected by export licenses. We then aggregate the industry-level export licenses at the prefecture level, weighted by

[13]For the depreciation rate, we use each firm's real depreciation rate provided by the NBSC firm-production database.

[14]Prior to China's joining of the WTO, firms exported either by obtaining export licenses or trade intermediaries. Export licenses were gradually phased out, and eventually, all firms became eligible to export directly by 2004 (Bai et al., 2017).

industry-level export value in each prefecture. We use data from Brambilla et al. (2010) and Handley and Limao (2017) to construct an HS6 digit-level indicator for Multi-Fiber Agreement on Textiles and Clothing (MFA) quotas. In particular, products are classified into 2 groups, one with a binding export quota and one without. We use their data and calculate the ratio of the products that were bound by quotas in each industry. We aggregate the industry-level index at the prefecture level. For the import tariffs imposed by China, we first collect the HS 6-digit-level MFN tariff from the WITS data set and calculate the import tariff rates at the prefecture level. Foreign direct investment (FDI) plays an important role in promoting Chinese local development, and it is necessary to account for this policy change. Following Facchini et al. (2019), we use the contract intensity measure proposed by Nunn (2007). Since the contract intensity measure is at the 3 digit ISIC (revision 2) industry level, we first convert these classifications to the HS 6-digit product level using the concordance provided by WITS and then calculate the average contract intensity at the prefecture level.

Table 1 reports the summary statistics for a set of key variables used in our paper.

5 Empirical Results

5.1 Average effects

5.1.1 Main results

Table 2 shows the main effects of the reduction in uncertainty on firm production and SO2 emissions. Columns (1) to (2) present the effects on firm output; columns (3) to (4) show the effects on SO2 emissions; columns (5) to (6) focus on SO2 emission intensity. All regressions control for firm and year fixed effects. Odd columns add no further controls, whereas even columns additionally control for firm initial output and SO2 emissions interacted with year dummies, which addresses the concern that our estimated effects are confounded by different time paths in output and emissions by firms with different initial sizes or emission levels. Consistent with our model predictions, we find that the reduction in export policy uncertainty leads to higher levels of firm output. The difference impact between the regions at 90th percentile and the regions at 10th percentile of export policy uncertainty reduction is about 5.6 percent.[15] Moreover, a one standard deviation increase in pre-WTO export policy uncertainty leads to a 4.2 percent increase in output after WTO

[15]The pre-WTO uncertainty difference between the 90th and 10th percentiles are 0.087 (as reported in Table 1), and the marginal effect of uncertainty on output is 0.639 (as reported in Table 2).

entry.[16] This is comparable with our simulated results in Section 3.5. The effect on SO2 emissions is negative but statistically insignificant. As a result of the positive effects on firm output and the insignificant effects on SO2 emissions, we find that the reduction in export policy uncertainty causes lower levels of SO2 emission intensity for firms. A one-standard-deviation increase in pre-WTO export policy uncertainty leads to an 8.6 percent decrease in emission intensity in the post-WTO period. These results are consistent with the model when firms face an overall emission cap.

The identification strategy for equation (33) relies on the parallel trends assumption that the outcomes in different comparison groups would follow the same time trend in the absence of treatment. Our estimate of β would be biased if firms located in prefectures facing different extents of trade policy uncertainty prior to WTO accession follow different time paths. To support the parallel trends assumption, we conduct an event study that takes the following form:

$$y_{it} = \sum_{t=1998}^{2007} \beta_t Uncertainty_p \times \delta_t + \gamma X_{ct} + \sum_t \theta_t X_i \times \delta_t + \delta_t + \gamma_i + \epsilon_{it}, \tag{36}$$

All variables in equation (36) follow the same definition as those in equation (33). Rather than interacting $Uncertainty_p$ with a $Post_{it}$ dummy, we interact $Uncertainty_p$ with each of the year dummy variables, with 2001 being the benchmark year. The event study specification allows us to examine changes in the correlation between a prefecture's pre-WTO uncertainty and the outcome of interest over time, with each β_t measuring the difference in this correlation in year t relative to the year 2001. If the parallel trends assumption holds, then we expect the estimated β_ts to be approximately zero throughout the WTO period but experience a sharp change after WTO accession.

We test this assumption separately for firm output and emission intensity following equation (36). We present the estimated coefficients and the 95 percent confidence intervals for firm output and emission intensity in Figures (5a) and (5b), respectively. In all figures, the benchmark year is 2001. We find that before 2001, the estimated coefficients are indistinguishable from zero. Moreover, the effect on output and SO2 intensity starts in 2001.

5.1.2 Robustness

In this subsection, we employ several empirical exercises to examine the sensitivity of the baseline estimates. Because our main variation is at the prefecture level, one concern is

[16] The standard deviation of uncertainty is 0.06545. We multiply the estimated coefficients by this number.

that our results are confounded by other concurrent events that occurred at the prefecture level. To address this concern, we further control for a set of prefecture variables. First, at the time of the WTO entry, China also changed its import tariffs, eliminated export licensing requirements, and faced different export quotas, and firms with different contract intensities also responded differently to WTO entry. We control for the value of these variables in 2000 at the prefecture level and interact them with the post dummy to address the concern that prefectures were affected differently by WTO accession along these dimensions. Second, we also control for contemporaneous prefecture GDP and population density. We present the results in Table 3 for firm output, SO2 emissions, and emission intensity. The results are highly consistent. In columns (1), (3), and (5), we control for the initial prefecture value of other policy changes interacted with the post dummy; in columns (2), (4), and (6), we further control for contemporaneous prefecture GDP per capita and population density. The effects on firm output, SO2 emissions and emission intensity remain largely consistent with those in Table 2, and the estimated coefficients are not influenced by additional contemporaneous prefecture controls, which suggests that our results are highly unlikely to be driven by other concurrent prefecture events.

Relatedly, firms with different ownership status or located in different provinces may experience different changes in production or SO2 emissions. One specific concern is that these differences are confounded by our uncertainty measure. We therefore address this concern by controlling for ownership-year fixed effects and province-year fixed effects and present the results in Table 4. Our results remain robust.

Another concern is that our main results are driven by the specific construct of the prefecture uncertainty measure. To show that our results are robust to the construction of the uncertainty measure, we use four alternative methods to construct the uncertainty measure. First, we use labor instead of exports as our weights and then compute the labor-weighted average value of the NTR gap at the prefecture level. To reflect the fact that Chinese exports to the U.S. experience a reduction in tariff uncertainty, we use product-level Chinese exports to the U.S. as our weights in the main exercise. This exercise, however, has two concerns. First, the Chinese exports to the U.S. are endogenous to U.S. policy, and our constructs using endogenous weights may cause biases. Second, this measure omits those exports from China to the U.S. via a third country or region such as Hong Kong. To demonstrate the robustness of our results, we use all product-level Chinese exports in our second and third measures. Our second measure uses the simple average NTR gap of all exports from a prefecture; the third measure uses the export-weighted average value of the NTR gap of a prefecture. We also calculate the firm-level trade policy uncertainty shock as fourth measures. As in the main exercise, we use the Chinese exports to the U.S. as our weights when we measure uncertainty at the firm level. Table 5 presents the results using different proxies for uncertainty. The first three columns of panel A use the first alternative uncertainty measure; the last three columns of panel A use the second alternative uncertainty measure; the first three columns of panel B use the third alternative uncertainty measure. In the last three columns of panel B, we define uncertainty at firm levels, which measures the uncertainty shock exerted on firms in more precise ways.[17] Notice that we have lost a significant number of observations using firm-level uncertainty measures. The results are highly consistent. The reduction in trade policy uncertainty significantly increased firm production, reduced firm overall emission of SO2, and reduced firm SO2 emission per unit of output.

5.1.3 Falsification Test

To rule out the possibility that our main results are spurious and driven by chance, we perform a falsification test. We follow equation (33) to conduct regression analyses based on randomly assigned false prefecture-level uncertainty to firms, in proportion to the actual uncertainty distribution. We then conduct 500 rounds of randomization and plot the distribution of estimated coefficients in Figure 6, separately for firm output in sub-figure (a) and firm SO2 emission intensity in sub-figure (b). For firm output, the mean value of the estimated coefficient is 0.0069, the standard deviation is 0.2355, and the actual estimate for firm output is depicted by the red vertical line valued at 0.639. For firm SO2 emission intensity, the mean value of the estimated coefficient is 0.0626, the standard deviation is 0.5817, and the actual estimate for firm output is depicted by the red vertical line valued at -1.313. Therefore, it is unlikely that the increases in firm output and declines in firm SO2 emission intensity reported in Table 2 are driven by chance.

5.2 Heterogeneous effects

To test Predictions 2 and 3, we examine the heterogeneous effects of reduced uncertainty on firm output and SO2 emissions varied by the strength of SO2 emission control. As we mention in Section 2, firms that are located in TCZs face more stringent SO2 emissions control than firms in non-TCZs. Thus, we expect that the reduction in export policy uncertainty should increase firm output in both TCZs and non-TCZs, but it would reduce firm emission intensity only for firms in TCZs.

[17] A prefecture may have firms that do not export to the U.S. Thus, defining uncertainty at prefecture levels is a less precise way to measure the policy uncertainty shock exerted on each firm.

We first separately study the average effects for firms in TCZs and non-TCZs following the main specification in equation (33). To further test the statistical significance of the effect difference, we conduct a triple-difference specification following equation (34).

Table 6 presents the results. Columns (1) to (3) study the effects on firm output. Column (1) focuses on firms in TCZs, and column (2) focuses on firms in non-TCZs. We find that the reduction in export policy uncertainty leads to increases of firm output in both TCZs (as shown in column (1)) and non-TCZs (as shown in column (2)). The triple-difference results presented in column (3) suggest insignificant differences in firm output increases in TCZs and non-TCZs.

Columns (4) to (6) rerun the exercises in columns (1) to (3) but replace the dependent variable with log value of firm SO2 emissions. We find that firm-level SO2 emissions in TCZs are significantly reduced when export policy uncertainty decreases (as shown in column (4)), whereas the firm-level SO2 emissions are unaffected in non-TCZs (as shown in column (5)). The triple-difference results presented in column (6) suggest that the effect difference in SO2 emissions between firms in TCZs and non-TCZs is significant at 5 percent.

Columns (7) to (9) further repeat the exercises with log values of firm SO2 emission intensity as the dependent variable. Consistent with the effects on firm SO2 emissions, we find that the reduction in export policy uncertainty significantly lowers SO2 emission intensity in TCZs but does not affect firms in non-TCZs. The difference of the effects on SO2 emission intensity is statistically significant at the 1 percent level.

We have also conducted the effects of reduced uncertainty on other pollution outcomes as our placebo check. Since the emission gap specifically targets SO2, the effects should not exist for other types of firm pollution. We use wastewater, fumes, and nitrogen oxides (NO_x) for our placebo check, as our dataset also covers these variables. Table 7 presents the results. All regressions control for firm and year fixed effects. In contrast to the results on SO2 in Tables 2, we do not find significant effects on the emission intensity of these types of pollution. Moreover, the trade policy uncertainty reduction exerts no heterogeneous effects on these alternative pollutants across regions with different SO2 emission control.

These results support our model predictions. When export policy uncertainty decreases, the overall emission control imposed on firms reduced per firm SO2 emissions and per firm SO2 emission intensity, but it does not affect firm output. One plausible explanation for why firm production (measured by firm output) is not influenced by the emission cap is that firms could improve production efficiency more in the regions with emission caps. We test the mechanisms in greater detail in the sections below.

5.3 Mechanism

Emission intensity declined following the reduction in export policy uncertainty, as shown in our previous analyses. It thus becomes natural to ask, what inherent mechanisms are accounting for this change? In particular, what accounts for the greater emission reduction for firms in TCZs? According to Liu et al. (2018), SO2 generated per unit of fossil fuel during the production process depends on conversion efficiency, desulfurization efficiency, and average sulfur content.[18] Therefore, we will analyze the underlying mechanisms from the perspective of the relative usage of fossil fuel (coal and fuel) and its sulfur content, pollution-control facilities and firm productivity in this section.

5.3.1 Effects on inputs

First, we study firms' use of energy in Table 8, separately for firms in TCZs and non-TCZs. Column (1) studies the average effect on coal use for all firms, whereas columns (2) and (3) split the sample and study the effect for firms in TCZs and non-TCZs. We find that, although the reduction in export policy uncertainty on average has a negative but statistically insignificant effect on coal use, the effects are drastically different for firms in TCZs and firms in non-TCZs. The reduction in uncertainty leads to a decline in coal use for firms in TCZs but an increase in coal use for firms in non-TCZs. The differences in the effects are statistically significant, as shown by the coefficient of the triple-interaction term in column (4).

We then repeat the exercises for fuel use. Column (5) studies the average effect on fuel use for all firms, whereas columns (6) and (7) split the sample and study the effect for firms in TCZs and non-TCZs. Consistent with the exercise on coal, we find that the reduction in uncertainty has an insignificant effect on fuel use on average, and the effects are different for firms in TCZs and firms in non-TCZs. The reduction in uncertainty leads to an insignificant decline in fuel use for firms in TCZs but a significant increase for firms in non-TCZs. The effect difference is statistically significant (column (8)).

Firms may also substitute away from fossil fuel to other inputs, such as non-polluting materials and labor. We then study the effect on other firm inputs in Table 9. Our dataset reports the total amount of intermediate inputs, which include energy input and material. For firms in TCZs, the reduced uncertainty causes a lower usage of energy but a possibly

[18] The emissions of SO2 can be expressed as $E_{SO_2} = \sum_{i,j} 2 \times C_j \times A_{i,j} \times S_{i,j} \times (1 - \eta_i)$ based on the mass balance method in Liu et al. (2018)), where E_{SO_2} represents the total emissions of SO_2; i and j represent power plant i and fuel type j, respectively; C_j is the conversion efficiency to sulfur dioxide from fuel type j; and $A_{i,j}$ is the annual consumption of fuel type j by power plant i. η_i is the desulfurization efficiency that varies across different de-SO_2 processes; $S_{i.j}$ represents the sulfur content in fuel j of plant i; and 2 represents the molecular weight of SO_2 that is twice the atomic weight of $S_{i,j}$.

higher use of material, while the effect on total intermediate inputs is ambiguous; firms in non-TCZs, the reduction in uncertainty promotes firm production and does not reduce energy use, and therefore, we expect the use of total intermediate inputs to increase. We present the results in columns (1) to (4). Columns (1) to (3) focus on all firms, firms located in TCZs and firms located in non-TCZs, respectively. The average effect on intermediate input use is statistically insignificant, as reported in column (1). Consistent with our expectation, we find that firms in non-TCZs increased their intermediate input use, whereas firms in TCZs did not significantly change intermediate input use.

The dataset also reports firm total labor employment. If labor is a substitute for fossil fuel, then reduced export policy uncertainty should cause firms in TCZs to increase their labor employment. For firms in non-TCZs, however, the expected effect is ambiguous. On the one hand, increases in production scale lead to a higher demand for labor; on the other hand, the higher labor demand in TCZs may drive up labor wages, which reduces demand for labor.[19] We report the results on labor in columns (5) to (8). We find that the reduction in uncertainty leads to higher overall labor employment for firms in our sample. The increases in labor are driven solely by firms in TCZs. There is no significant effect on firms in non-TCZs.

5.3.2 Effects on sulfur content and pollution abatement equipment

Firms may also change the types of coal and fuel to reduce emissions intensity. A more direct test would be to test the sulfur content used by firms. Moreover, the reduction in emission intensity can be also caused by more abatement equipment. We then examine the effects of reduced uncertainty on energy sulfur content and abatement equipment, which are two variables available in our dataset.

Table 10 presents the results. Columns (1) to (4) focus on the sulfur content of energy use, and columns (5) to (8) focus on pollution abatement equipment. We find that the firms in TCZs significantly reduced the sulfur content when they increased firm output as a response to the reduction in export policy uncertainty, and they also adopted more pollution-control facilities to remove sulfur emissions. These effects only exist for firms in TCZs and not for firms in non-TCZs. The significant heterogeneous effects are highlighted in the estimated coefficients of the triple-difference exercise in columns (4) and (8).

[19] Higher demand for labor in TCZs induces labor to be reallocated from non-TCZs to TCZs.

5.3.3 Effects on firm productivity

According to the Porter hypothesis, strict environmental regulations can induce firms to upgrade their productivity. We examine this by testing whether firms in TCZs improve productivity more when export policy uncertainty decreases. In Table 11, we use two different measures of TFP. Columns (1) to (4) use the Olley-Pakes method to compute firm TFP, while columns (4) to (8) use the ACF method to compute firm TFP. We follow the previous exercises and separately examine the average policy effects on firm TFP, the effects on firm TFP in TCZs and effects on firm TFP in non-TCZs. In columns (1) and (5), we show the average effects. We find that the reduction in export policy uncertainty leads to a higher level of firm TFP.[20] We also find that the productivity-improving effects of lower uncertainty are greater for firms in TCZs, which is consistent with our results in Table 6 that after export policy uncertainty decreases, firms in TCZs and non-TCZs increase firm output by comparable magnitudes, but only firms in TCZs reduce SO2 emissions intensity.

6 Conclusion

This study examines the effects of reducing the uncertainty of trade policy on firms' pollution behavior. We first develop a model to show that the impacts of reducing trade policy uncertainty on firms' pollution behavior depend on whether an emission cap exists. When a cap exists, reduced uncertainty leads to higher output but lower emission intensity. When no cap exists, however, reduced uncertainty increases firm output but has no effect on emission intensity. We exploit spatial variations in the reductions in trade policy uncertainty caused by U.S. conferral of PNTR status to Chinese exporters and variations in emission control caused by the TCZs to test the hypotheses. Our empirical evidence is consistent with the model predictions. We find that the reduction in uncertainty increases firm output by comparable magnitudes across regions with different extents of emission control, but it reduces firm SO2 emission intensity and total firm SO2 emissions only in regions with stringent emission control. The decline in SO2 emissions is caused by reduced use of fossil fuel, less sulfur content in energy use, and more abatement equipment, and firms substitute away from energy use with more labor. We also find that the reduction in uncertainty and emission control jointly improve firms' productivity, consistent with the Porter hypothesis. One implication is that it is not imperative for developing countries to adopt lax environmental regulations to capture gains from globalization. Instead,

[20] This is consistent with the literature on trade-induced technological upgrading; see, e.g., Bustos (2011).

strengthening environmental regulations may promote production efficiency for firms in developing countries in times of globalization.

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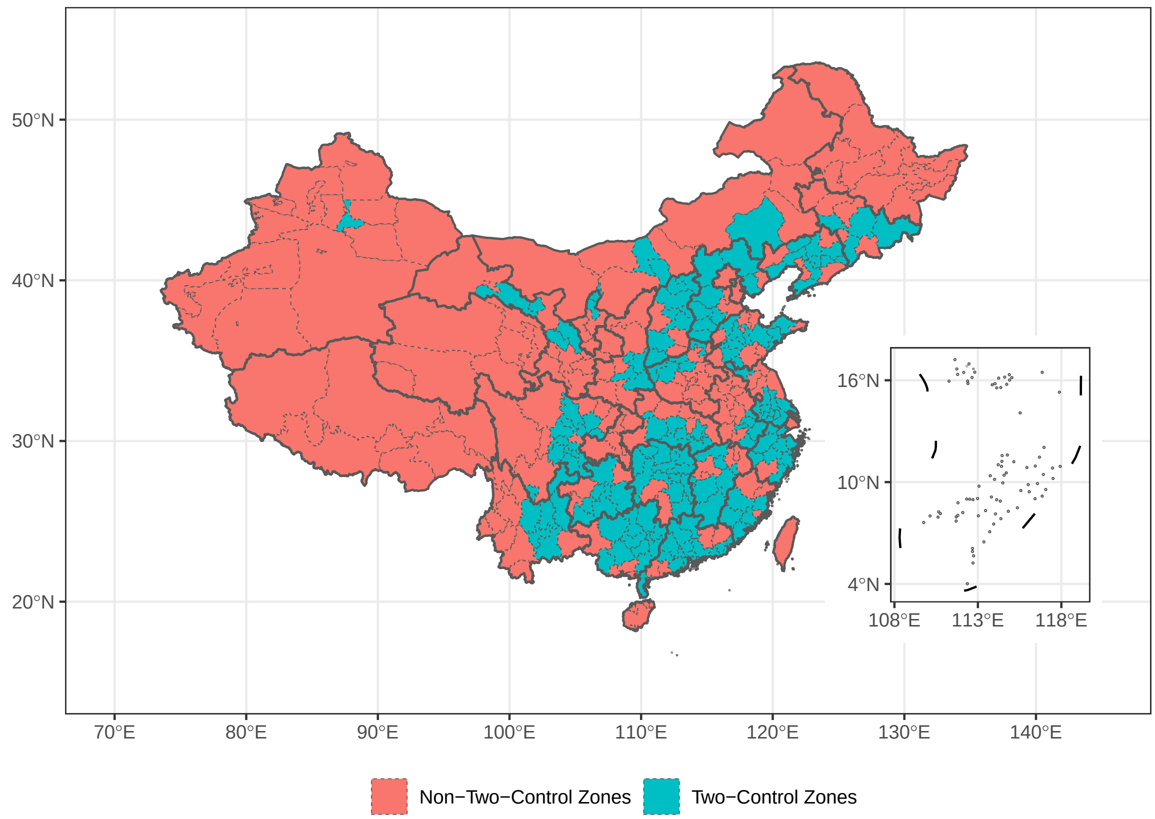


Figure 1: Geographic Locations of Two-Control Zones and Non-Two-Control Zones

Notes: This figure presents the geographic locations of prefectures in the two-control zones (colored in red) and prefectures in the non-two-control zones (colored in blue).

Figure 2: Total Output and SO2 Emission in Two-Control Zones and Non-Two-Control Zones

Notes: This figure plots the total GDP and total SO2 emission in two-control-zones (TCZs) and non-two-control-zones (non-TCZs). The data for GDP are drawn from CEIC database, and the SO2 emission data are from China Statistical Yearbook on Environment, published by the Ministry of Ecology and Environment of China. We treat 1999 as the benchmark year (value=100). Although GDP has been rising rapidly in both regions, the SO2 emission in TCZs remains relatively stagnant between 1999 and 2006, which reveals a relatively more stringent SO2 emission control.

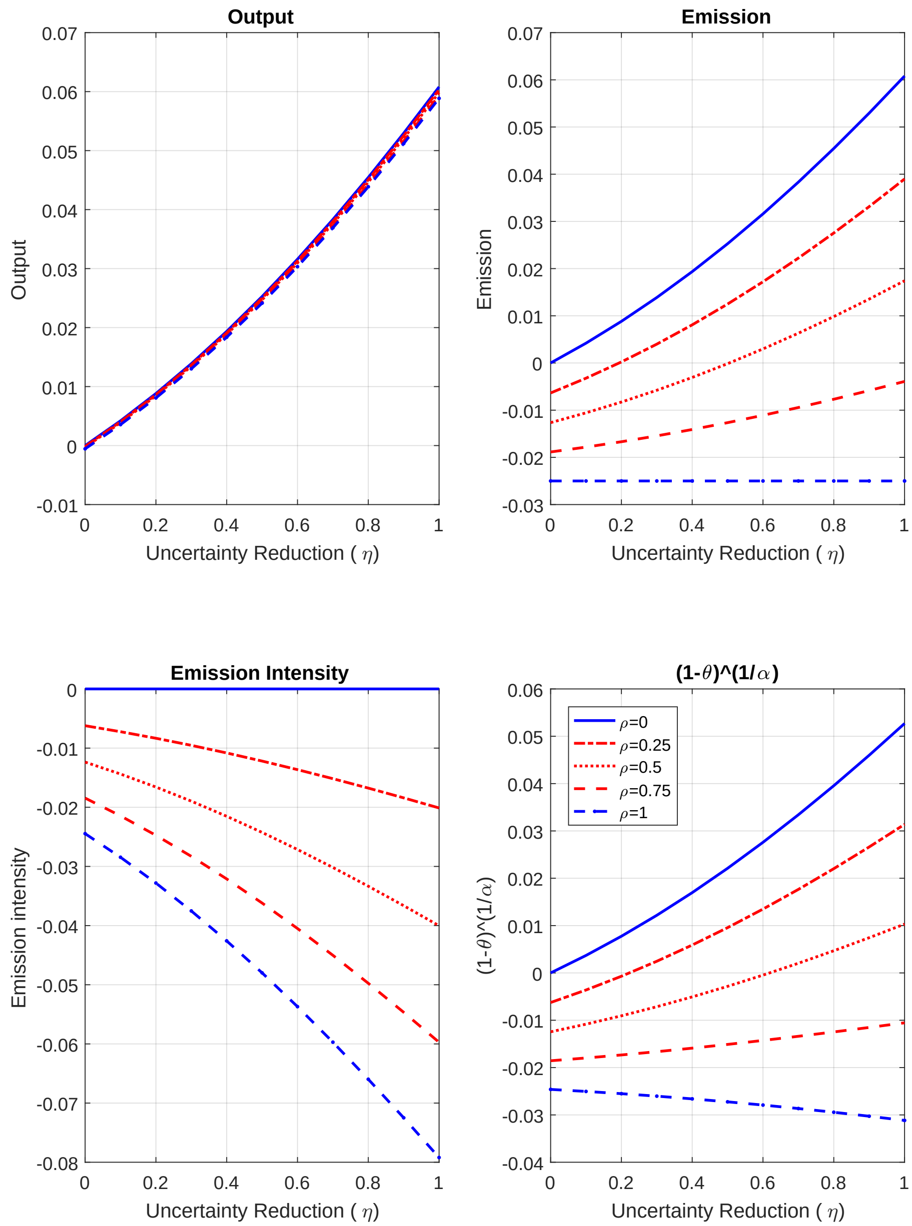


Figure 3: The Simulated Effects of Uncertainty Reduction on Production and Emission (Emission Cap $\kappa = 0.975$)

Notes: This figure presents the simulated effects of a reduction in export policy uncertainty on firm total output, total emission, emission intensity, and inputs used for production, respectively. We set the emission cap κ to be 0.975. We plots the effects for different levels of environment regulation stringency, characterized by parameter ρ. A higher value of ρ corresponds to more stringent emission control.

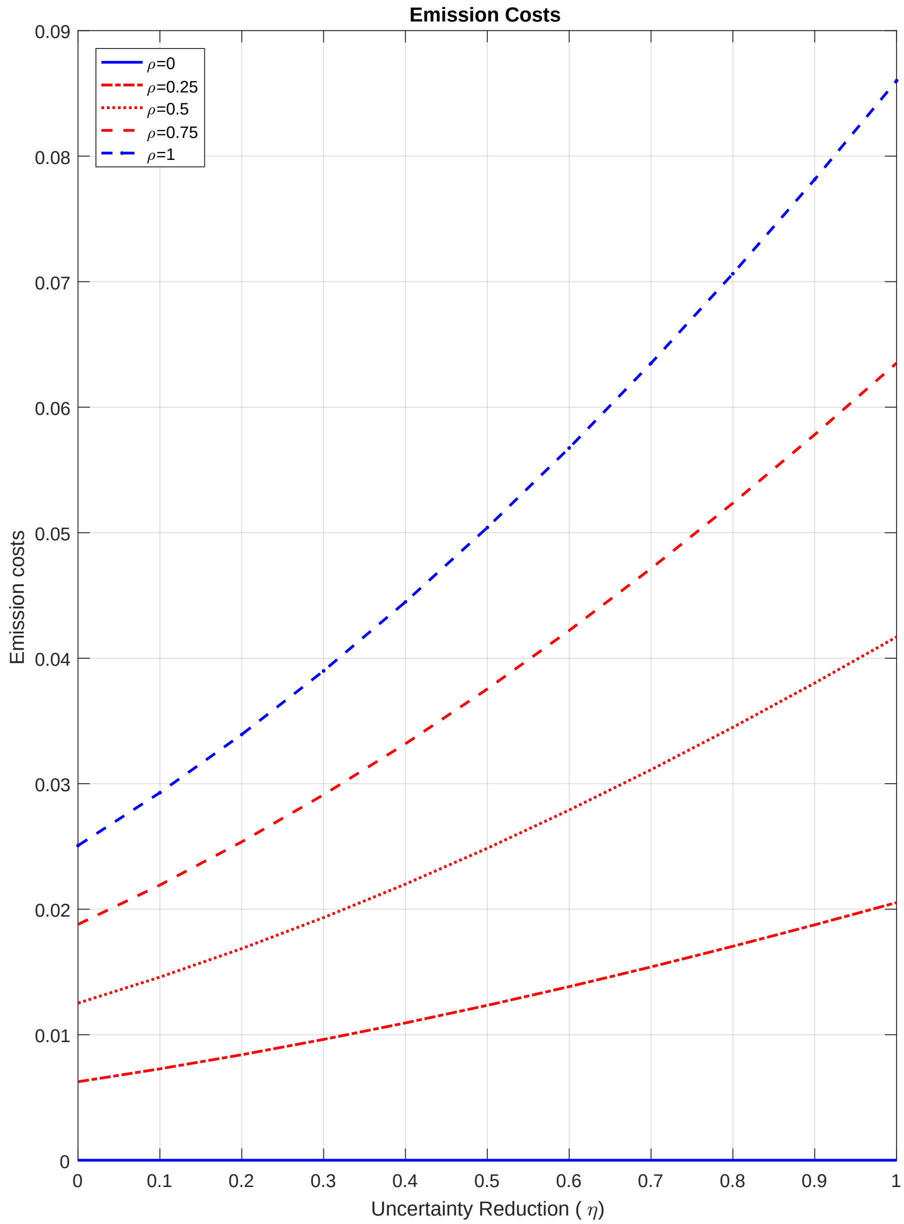
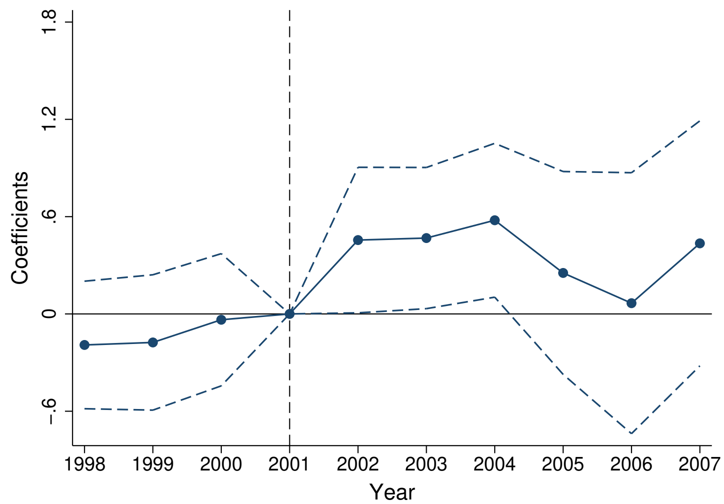
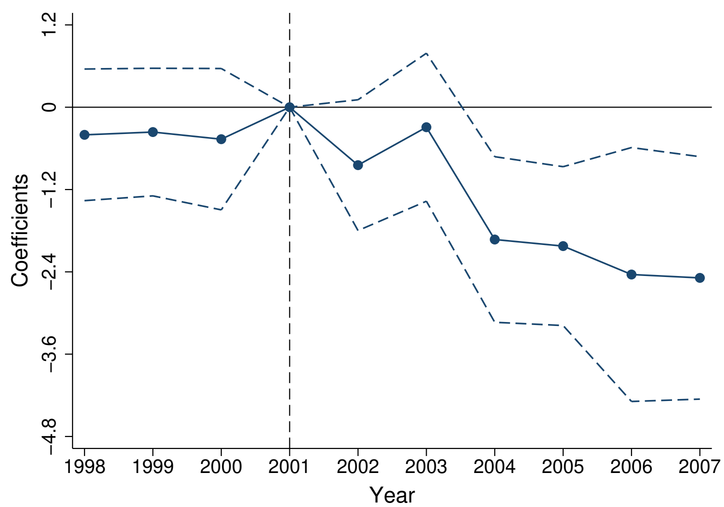


Figure 4: The Simulated Effects of Uncertainty Reduction on Emission Costs (Emission Cap $\kappa = 0.975$)

Notes: This figure presents the simulated effects of a reduction in export policy uncertainty on firm emission costs. We set the emission cap κ to be 0.975. We plots the relations between uncertainty reduction and emission cost for different levels of environment regulation stringency, which is characterized by ρ. A higher value of ρ corresponds to more stringent emission control.



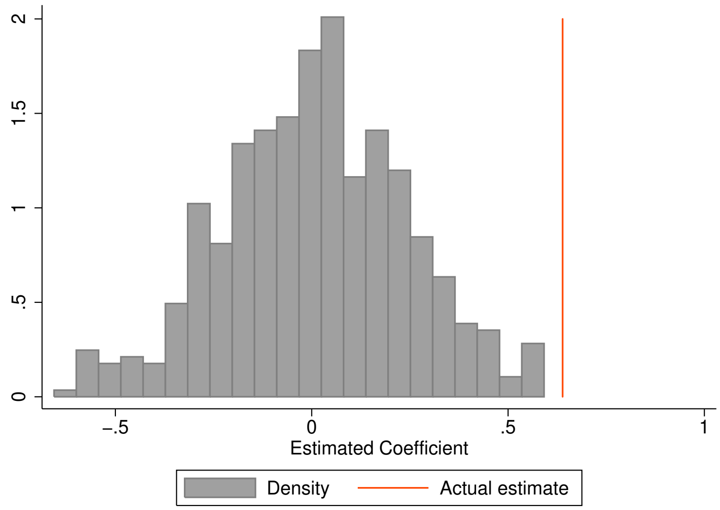
(a) Firm Output



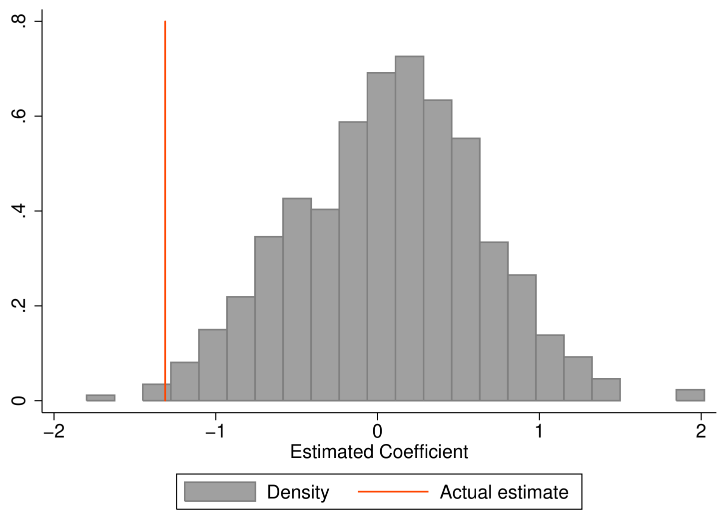
(b) Firm SO2 Intensity

Figure 5: Dynamic Effects of Uncertainty Reduction

Notes: This figure show the dynamic effects of export policy uncertainty reduction on firm output, and SO2 intensity, respectively in subfigure (a), and (b). We run the following regression, $y_{it} = \sum_{t=1998}^{2007} \beta_t Uncertainty_p \times \delta_t + \gamma X_{pt} + \sum_t \theta_t X_i \times \delta_t + \delta_t + \gamma_i + \epsilon_{it}$, where y_{it} respectively refers to log sales and log SO2 intensity of firm i in year t. $Uncertainty_p$ is the pre-WTO export policy uncertainty of prefecture. δ_t and δ_i are year and firm fixed effects, respectively. X_{pt} include prefecture contemporaneous controls and X_i denotes firm pre-WTO controls. We cluster standard error at the prefecture-year level. The solid line connects all estimates of β_t where 2001 is the benchmark year; the dashed lines represent the 95 percent confidence intervals.



(a) Firm Output



(b) Firm SO2 Intensity

Figure 6: Distribution of estimates in 500 randomization tests

Notes: In this exercise, we follow equation (33) to conduct regression analyses based on randomly assigned uncertainty. We assign false prefecture-level uncertainty to firms randomly in proportion to the actual uncertainty distribution. We then conduct 500 rounds of randomization and plot the distribution of estimated coefficients in the figures above, separately for firm output and firm SO2 emission intensity. For firm output, the mean value of estimated coefficient is 0.0069 and the standard deviation is 0.2355, and the actual estimate for firm output is depicted by the red vertical line valued at 0.639. For firm SO2 emission intensity, the mean value of estimated coefficient is 0.0626 and the standard deviation is 0.5817, and the actual estimate for firm output is depicted by the red vertical line valued at -1.313.

Table 1: Summary Statistics

Variable	Obs	Mean	Std.Dev.	P10	P50	P90
Dependent Variables						
Log Output	58979	8.007	1.607	6.205	7.895	10.050
Log SO2 Emission	58979	10.050	2.065	7.455	10.150	12.500
Log SO2 Emission Intensity	58979	2.038	2.129	-0.676	2.239	4.504
Log Wastewater Intensity	51623	2.909	1.962	0.425	3.010	5.317
Log Fumes Intentsity	54971	1.697	2.702	-1.609	1.594	5.409
Log NOx	17957	-6.561	4.235	-10.370	-7.871	1.216
Log Coal	53607	6.715	2.571	3.714	7.080	9.398
Log Fuel	13275	3.800	3.237	0.000	4.078	8.075
Log Facilities	52398	1.143	0.803	0.000	1.099	2.197
Sulfur Content	13154	0.132	0.642	0.000	0.000	0.580
Log Employment	58836	5.951	1.111	4.605	5.886	7.378
Log Intermediate Inputs	58698	10.220	1.542	8.465	10.100	12.200
TFP(OP)	58495	0.781	1.458	-1.373	1.045	2.399
TFP(ACF)	58495	3.892	1.812	2.203	3.487	6.303
Independent Variables						
Uncertainty(Base)	58979	0.054	0.047	0.005	0.049	0.092
Uncertainty(All Exp. Weighted)	58979	0.346	0.115	0.182	0.371	0.490
Uncertainty(Employment Weighted)	65011	0.244	0.069	0.142	0.256	0.320
Uncertainty(Simple Avg.)	58979	0.392	0.084	0.297	0.405	0.472
Uncertainty(Firm Level)	8221	0.018	0.065	0.000	0.000	0.030
Initial Log Output	58979	7.910	1.480	6.215	7.824	9.810
Initial Log SO2 Emission	58979	10.180	2.033	7.659	10.290	12.600
SOE (=1 if SOE)	58979	0.389	0.487	0.000	0.000	1.000
Log GDP per capita	58522	9.295	0.810	8.335	9.223	10.390
Log pop	58522	6.049	0.677	5.233	6.118	6.775
TCZ (=1 if TCZ)	58979	0.744	0.437	0.000	1.000	1.000
Import Tariff	58439	15.010	8.205	8.464	14.130	20.790
Export License	58699	0.166	0.273	0.009	0.042	0.597
Contract Intensity	58979	0.509	0.113	0.344	0.528	0.630
Export Quota	58979	0.156	0.141	0.006	0.139	0.333

Table 2: Average Policy Effects on Firm Output and SO2 Emission

	Output		SO2 Emission		SO2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty $\times$ Post	0.516***	0.639***	-0.538	-0.674	-1.054***	-1.313***
	(0.175)	(0.183)	(0.420)	(0.412)	(0.397)	(0.395)
Firm-level Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.853	0.855	0.762	0.774	0.742	0.756
Observation	58979	58979	58979	58979	58979	58979

Notes: The dependent variable in columns (1)-(2) is the (log) output, in columns (3)-(4) is the (log) SO2 emission, and in columns (5)-(6) is the (log) SO2 emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 3: Average Policy Effects Controlling For Contemporaneous Prefectural Controls

	Output		SO2 Emission		SO2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty $\times$ Post	0.806***	0.767***	-0.218	-0.215	-1.024**	-0.982**
	(0.186)	(0.184)	(0.417)	(0.421)	(0.402)	(0.405)
Log GDP per capita		0.095***		0.008		-0.088
		(0.028)		(0.075)		(0.085)
Log pop		0.058**		0.036		-0.022
		(0.024)		(0.048)		(0.047)
City-level Shocks	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.855	0.855	0.776	0.777	0.756	0.756
Observation	58439	58439	58439	58439	58439	58439

Notes: The dependent variable in columns (1)-(2) is the (log) output, in columns (3)-(4) is the (log) SO2 emission, and in columns (5)-(6) is the (log) SO2 emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. City-level shocks include import tariffs, export licensing, export quotas, and contract intensities interacted with year dummies. Robust standard errors are clustered at the prefecture-year level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 4: Robustness Checks: Policy Effects with More Fixed Effects

	Output		SO2 Emission		SO2 Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty $\times$ Post	0.629***	0.681***	-0.845**	-0.827**	-1.474***	-1.509***
	(0.183)	(0.203)	(0.413)	(0.389)	(0.396)	(0.383)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.855	0.856	0.775	0.780	0.756	0.762
Observation	58979	58979	58979	58979	58979	58979

Notes: The dependent variable in columns (1)-(2) is the (log) output, in columns (3)-(4) is the (log) SO2 emission, and in columns (5)-(6) is the (log) SO2 emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 5: Policy Effects using Alternative Constructs of Trade Policy Uncertainty

Panel A: Alternative Measures of Uncertainty (Employment Weighted and All Export Weighted)						
	Uncertainty (Employment Weighted)			Uncertainty (All Export Weighted)		
	Output	SO2 Emission	Intensity	Output	SO2 Emission	Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty × Post	0.222*	-1.273***	-1.495***	0.125*	-0.237	-0.362**
	(0.124)	(0.254)	(0.260)	(0.075)	(0.157)	(0.160)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.857	0.855	0.855	0.750	0.756	0.755
Observation	58979	58979	58979	58979	58979	58979
Panel B: Alternative Measures of Uncertainty (Simple Weighted and Firm-level Uncertainty)						
	Uncertainty (Simple Average)			Uncertainty (Firm-level)		
	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty × Post	0.180*	-0.608***	-0.787***	0.460**	-1.208**	-1.668***
	(0.102)	(0.206)	(0.208)	(0.230)	(0.526)	(0.526)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.766	0.774	0.774	0.848	0.826	0.764
Observation	58979	58979	58979	7705	7705	7705

Notes: The dependent variable in columns (1) and (4) is the (log) output, in columns (2) and (5) is the (log) SO2 emission, and in columns (3) and (6) is the (log) SO2 emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output. Columns (1), (2) and (3) in panel A use alternative uncertainty measure 1; columns (4), (5) and (6) in panel A use alternative uncertainty measure 2; columns (1), (2) and (3) in panel B use alternative uncertainty measure 3; columns (4), (5) and (6) in panel B use firm-level uncertainty measure. All these three prefecture-year measures are constructed by using the year 2000 China export data across all destinations. Robust standard errors are clustered at the prefecture-year level in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 6: Heterogeneity Policy Effects by Two-Control-Zones (TCZ)

	Output			SO2 Emission			SO2 Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uncertainty $\times$ Post	0.767***	0.508**	0.495**	-2.293***	0.330	0.301	-1.526**	-0.178	-0.194
	(0.284)	(0.232)	(0.231)	(0.618)	(0.402)	(0.419)	(0.659)	(0.414)	(0.425)
Uncertainty $\times$ Post $\times$ TCZ			0.266			-1.896**			-2.162***
			(0.368)			(0.781)			(0.757)
Post $\times$ TCZ			0.003			0.046			0.043
			(0.026)			(0.056)			(0.056)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adkj. R-square	0.860	0.836	0.855	0.765	0.756	0.774	0.780	0.722	0.756
Observation	43871	15108	58979	43871	15108	58979	43871	15108	58979

Notes: Columns (1), (4) and (7) use subsample of TCZ; columns (2), (5) and (8) use subsample of non-TCZ; columns (3), (6) and (9) use whole sample, The dependent variable in columns (1)-(3) is the (log) output, in columns (4)-(6) is the (log) SO2 emission, and in columns (7)-(9) is the (log) SO2 emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 7: Policy Effects on Other Firm Pollutants

	Wastewater Intensity				Fumes Intensity				NOx Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	TCZ	non-TCZ	All	All	TCZ	non-TCZ	All	All	TCZ	non-TCZ	All
Uncertainty $\times$ Post	-0.047	0.241	-0.278	-0.242	-0.404	-0.893	0.197	0.172	-1.017	-0.287	-1.293	-1.426
	(0.316)	(0.475)	(0.413)	(0.426)	(0.422)	(0.606)	(0.533)	(0.533)	(0.709)	(1.039)	(0.910)	(0.938)
Uncertainty $\times$ Post $\times$ TCZ				0.365				-1.065				1.051
				(0.638)				(0.808)				(1.398)
Post $\times$ TCZ				-0.007				-0.022				-0.249***
				(0.046)				(0.071)				(0.094)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.756	0.755	0.757	0.756	0.811	0.820	0.773	0.811	0.883	0.880	0.893	0.883
Observation	47602	35329	12273	47602	50972	37578	13394	50972	17840	14115	3725	17840

Notes: The specifications (2), (6) and (10) use subsample of TCZ; specifications (3), (7) and (11) use subsample of non-TCZ; specifications (1), (4), (5), (8), (9) and (12) use whole sample, The dependent variable in specifications (1)-(4) is the (log) wastewater emission intensity, in specifications (5)-(8) is the (log) fume emission intensity, and in specifications (9)-(12) is the (log) nitrogen oxides emission intensity. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors corrected for clustering at the city-year level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 8: Policy Effects on Energy Use

	Coal				Fuel			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	TCZ	non-TCZ	All	All	TCZ	non-TCZ	All
Uncertainty × Post	-0.293	-1.483*	1.288***	1.198**	0.973	-1.333	5.668***	5.401***
	(0.515)	(0.787)	(0.475)	(0.529)	(1.313)	(1.569)	(1.998)	(2.000)
Uncertainty × Post × TCZ				-2.842***				-6.932***
				(0.964)				(2.552)
Post × TCZ				-0.097				0.786***
				(0.062)				(0.196)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adkj. R-square	0.932	0.927	0.947	0.932	0.652	0.661	0.584	0.653
Observation	53607	39165	14442	53607	13275	11342	1933	13275

Notes: Columns (1), (4), (5) and (8) use whole sample; columns (2) and (6) use subsample of firms in TCZs; columns (3) and (7) use subsample of firms in non-TCZs. The dependent variable in columns (1)-(4) is the (log) consumption of coal, in columns (5)-(8) is the (log) consumption of fule. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses*** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 9: Policy Effects on Employment and Intermediate Inputs

	Intermediate Inputs				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	TCZ	Non-TCZ	All	All	TCZ	Non-TCZ	All
Uncertainty × Post	0.193	-0.104	0.553***	0.537***	0.368***	0.642***	0.124	0.132
	(0.171)	(0.258)	(0.199)	(0.199)	(0.115)	(0.172)	(0.144)	(0.147)
Uncertainty × Post × TCZ				-0.670**				0.491**
				(0.325)				(0.226)
Post × TCZ				0.020				-0.033**
				(0.025)				(0.016)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.899	0.905	0.876	0.899	0.912	0.914	0.904	0.912
Observation	58698	43671	15027	58698	58836	43765	15071	58836

Notes: Columns (1), (4), (5) and (8) use whole sample; columns (2) and (6) use subsample of firms in TCZs; columns (3) and (7) use subsample of firms in non-TCZs. The dependent variable in columns (1)-(4) is the (log) intermediate inputs, in columns (5)-(8) is the (log) employment. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO_2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses*** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 10: Policy Effects on Sulfur Content and Pollution-control Facility

	Sulfur content				Facility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	TCZ	non-TCZ	All	All	TCZ	non-TCZ	All
Uncertainty × Post	-0.357**	-0.643**	-0.112	-0.132	0.343***	0.671***	0.046	0.042
	(0.143)	(0.281)	(0.089)	(0.112)	(0.129)	(0.210)	(0.147)	(0.146)
Uncertainty × Post × TCZ				-0.512*				0.607**
				(0.295)				(0.257)
Post × TCZ				0.061**				-0.026
				(0.025)				(0.021)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adkj. R-square	0.510	0.494	0.744	0.510	0.736	0.745	0.703	0.736
Observation	13154	9918	3236	13154	52398	38819	13579	52398

Notes: Columns (1), (4), (5) and (8) use whole sample; columns (2) and (6) use subsample of firms in TCZs; columns in (3) and (7) use subsample of firms in non-TCZs. The dependent variable in columns (1)-(4) is the sulfur content of coal, in columns (5)-(8) is the (log) number of off-gas treatment facilities. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 11: Policy Effects on Firm Total Factor Productivity

	TFP(OP)				TFP (ACF)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	TCZ	Non-TCZ	All	All	TCZ	Non-TCZ	All
Uncertainty $\times$ Post	0.443***	0.764***	0.060	0.051	0.584***	0.739***	0.357*	0.352*
	(0.154)	(0.226)	(0.202)	(0.204)	(0.166)	(0.257)	(0.196)	(0.199)
Uncertainty $\times$ Post $\times$ TCZ				0.737**				0.410
				(0.310)				(0.329)
Post $\times$ TCZ				-0.004				0.014
				(0.022)				(0.024)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-square	0.852	0.856	0.839	0.852	0.885	0.893	0.852	0.885
Observation	58495	43536	14959	58495	58495	43536	14959	58495

Notes: The specifications (1), (4), (5) and (8) use whole sample; specifications (2) and (6) use subsample of TCZ; specifications (3) and (7) use subsample of non-TCZ. The dependent variable in specifications (1)-(4) is the TFP calculated by OP method, in specifications (5)-(8) is the TFP of ACF version. Firm-level controls refer to the interactions between the year dummies and each firm's initial output, as well as their initial SO2 emission. Robust standard errors are clustered at the prefecture-year level in parentheses*** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Appendix

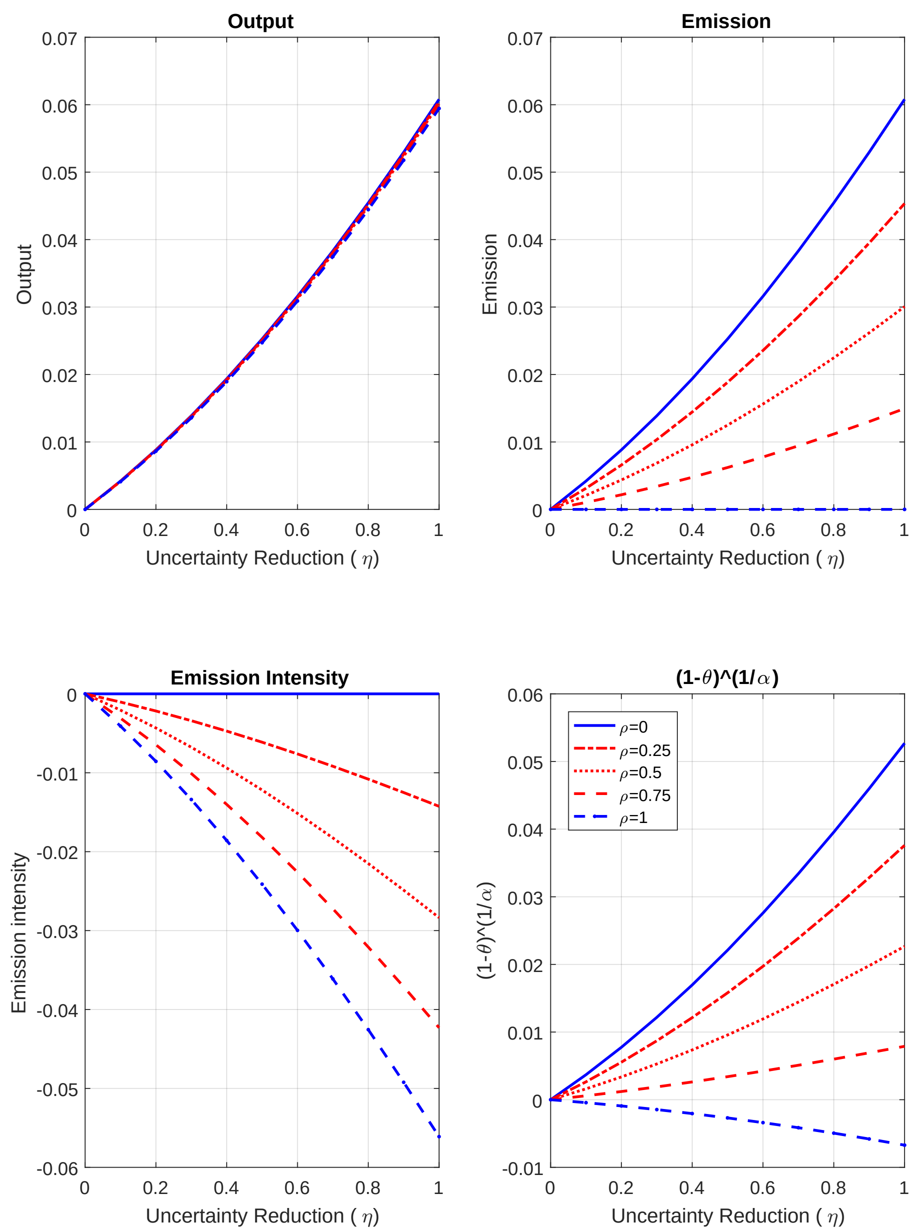


Figure A.1: The Simulated Effects of Uncertainty Reduction on Firm Production and Emission (Emission Cap $\kappa = 1$)

Notes: This figure presents the simulated effects of a reduction in export policy uncertainty on firm total output, total emission, emission intensity, and inputs used for production, respectively. We set the emission cap κ to be 1. We plots the effects for different levels of environment regulation stringency, characterized by parameter ρ. A higer value of ρ corresponds to more stringent emission control.

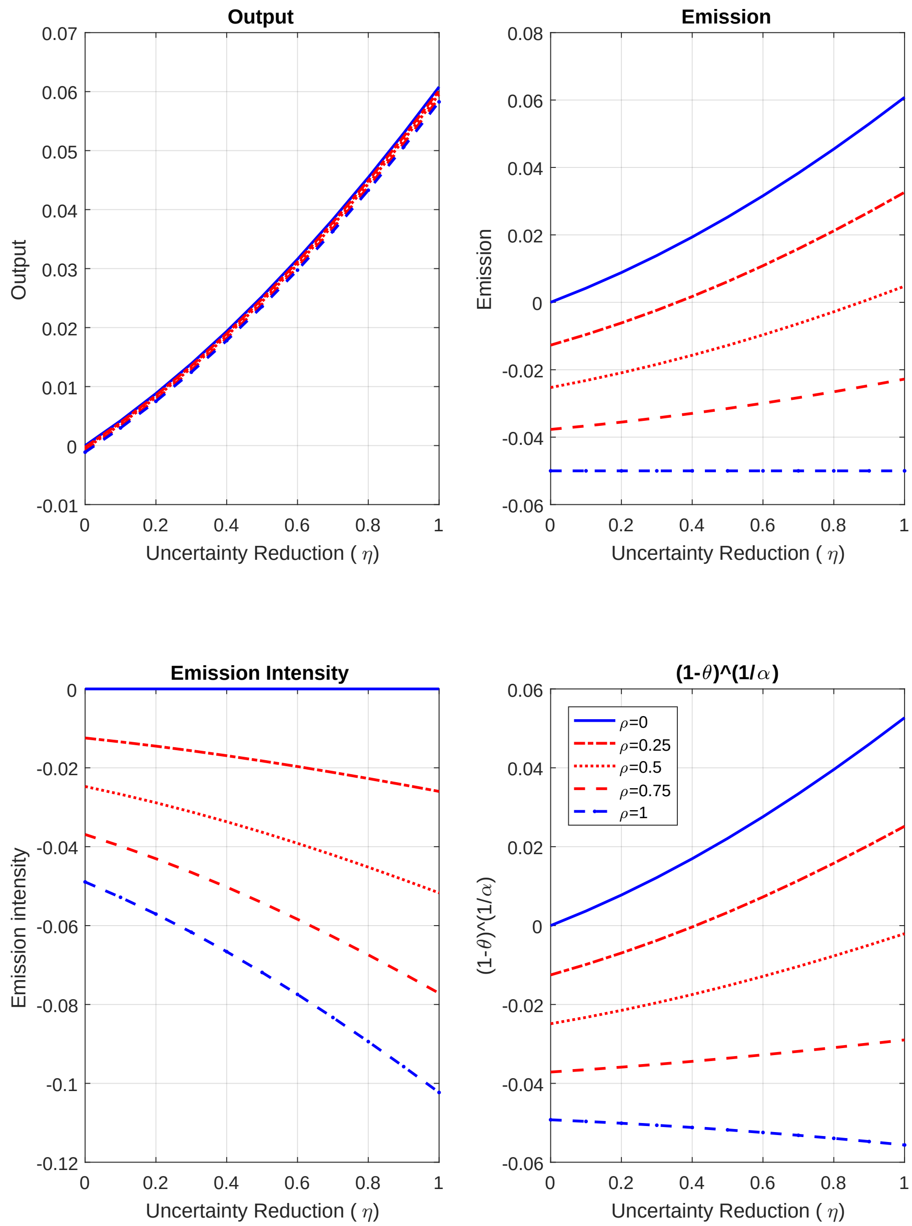


Figure A.2: The Simulated Effects of Uncertainty Reduction on Firm Production and Emission (Emission Cap $\kappa = 0.95$)

Notes: This figure presents the simulated effects of a reduction in export policy uncertainty on firm total output, total emission, emission intensity, and inputs used for production, respectively. We set the emission cap κ to be 0.95. We plots the effects for different levels of environment regulation stringency, characterized by parameter ρ. A higer value of ρ corresponds to more stringent emission control.