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ARTICLE

How does trade policy uncertainty affect firms' pollution emissions? Theory and evidence from China

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Abstract

The literature investigates trade-environment relationship at the firm level, but does not focus on the environmental effect of trade policy uncertainty. In the context of de-globalization and Sino-US trade friction, trade policy uncertainty significantly increases. How does trade policy uncertainty affect firms' pollution emissions? In this study, we incorporate energy, pollution, and trade policy uncertainty into Melitz's (2003) framework and construct a theoretical model to reveal the relationship between trade policy uncertainty and pollution emissions. Then, we employ the event that the USA granted permanent normal trade relationship to China as a quasi natural experiment. We use difference-in-difference-in-difference model and the data of Chinese manufacturing firms for empirical analysis. Our results indicate that the decrease in trade policy uncertainty reduces emission intensity of exporting firms, but has no significant impact on emission levels. Given that these firms do not aggravate emission levels under the condition of expanding output scale, we conclude that the decrease in trade policy uncertainty can improve environmental performance. Mechanism analysis shows an interesting finding that the decrease in trade policy uncertainty reduces emission intensity mainly by improving energy efficiency rather than improving abatement technology and optimizing energy structure. In addition, pollution reductions mainly occur in pollution-intensive and capital-intensive industries as well as coastal regions. Altogether, this study contributes to the literature on trade-environment relationship and trade policy uncertainty.

Keywords: Trade policy uncertainty; pollution emissions; energy efficiency; heterogeneous firms

1. Introduction

The relationship between trade and environment is a longstanding and challenging topic. International trade is regarded as one of the most important factors affecting environmental pollution (Antweiler et al. 2001; Shapiro and Walker, 2018). The early literature indicates that trade leads to changes in environmental pollution of various countries (Copeland and Taylor, 1994; Antweiler et al. 2001). The recent literature investigates this relationship at the firm level, and firm-level works can better reveal the mechanism by which trade affects pollution emissions (Cherniwchan, 2017; Cherniwchan et al. 2017). However, these works are studied from the perspective of free trade or globalization, focusing on the environmental effects of trade liberalization (Cherniwchan, 2017; Gutiérrez and Teshima, 2018), export behavior (Forslid et al. 2018; Rodrigue et al. 2022a), and import behavior (Imbruno and Ketterer, 2018; He and Huang, 2022). In recent years, with the emergence of de-globalization and Sino-US trade friction, the uncertainty of trade policy significantly increases (He et al. 2020c; Benguria et al. 2022). Different from free trade policies, such as trade liberalization and promoting imports and exports, trade policy uncertainty caused by trade protection inevitably has differentiated effects on pollution emissions. However, the literature does not pay sufficient attention to the environmental effect of trade policy uncertainty. Therefore, it is crucial to study how trade policy uncertainty affects firms' pollution emissions.

According to Pierce and Schott (2016), trade policy uncertainty refers to that external trade policies (such as tariff) are uncertain in the future, which corresponds to an increase in expected trade costs faced by firms. Firms are major exporters and pollution emitters. Their behaviors and performances are significantly influenced by trade policy uncertainty (Pierce and Schott, 2016; Handley and Limão, 2017). Handley and Limão (2015, 2017) indicate that the decrease in trade policy uncertainty reduces expected trade costs and marginal costs of exporting firms, leading to more exports and output expansion. It further enables firms to invest in technology upgrading (Liu and Ma, 2020). On the one hand, both exports and technology upgrading are conducive to improving energy efficiency and thereby reducing emission intensity (Shapiro and Walker, 2018; Forslid et al. 2018). On the other hand, larger output scale results in the higher level of pollution emissions (Cherniwchan, 2017; Rodrigue et al. 2022b). As a consequence, the impact of trade policy uncertainty on firm-level pollution emissions is complex. However, the literature does not give an answer to this impact. In this study, we focus on answering the following questions: Does trade policy uncertainty aggravate or reduce firms' pollution emissions? Through which mechanisms? This study not only contributes to the literature on trade-environment relationship and trade policy uncertainty but also provides implications in the context of de-globalization and Sino-US trade friction.

To reveal how trade policy uncertainty affects pollution emissions, we construct a theoretical model based on Melitz's (2003) framework. We expand Melitz's (2003) framework by incorporating energy and pollution and introducing trade policy uncertainty referring to Handley and Limão (2017). Given that the decrease in trade policy uncertainty reduces expected trade costs, it enables firms to invest in production technology and thereby improve energy efficiency. We regard energy efficiency as a special channel to analyze how trade policy uncertainty affects emission intensity and emission levels. As the results of theoretical analysis, we deduce three propositions. First, the decrease in trade policy uncertainty reduces emission intensity of exporting firms. Second, the impact of trade policy uncertainty on emission levels is uncertain, depending on the changes in emission intensity and output scale. Third, improving energy efficiency is an important mechanism for reducing emission intensity.

Then, we follow Pierce and Schott (2016) to employ the event that the USA granted permanent normal trade relationship (PNTR) to China as a quasi natural experiment. Before China's accession to the WTO, the US Congress annually voted on whether to impose MFN tariff (with lower tariff rate) or column 2 tariff (with higher tariff rate) on Chinese products. After joining the WTO, China was granted PNTR by the USA in 2002. Since then, Chinese products can annually apply to MFN tariff. This event evidently reduces trade policy uncertainty faced by Chinese firms, which provides an exogenous shock to identify the variation in uncertainty (Pierce and Schott, 2016; Handley and Limão, 2017). In addition, China and the USA are the two largest economies in the world. Their relationship is always the focus of the world. Thus, this event is an excellent case to study the impact of trade policy uncertainty.

We employ the data of Chinese manufacturing firms for empirical analysis. We construct a difference-in-difference-in-difference (DDD) model to examine the causal effect of decrease in trade policy uncertainty on firms' pollution emissions. Besides, we employ the distance from located city to the nearest port and exchange rate as instrumental variables (IV) of exporting. Our conclusion indicates that the decrease in trade policy uncertainty can reduce emission intensity of exporting firms. To explore how the decrease in trade policy uncertainty reduces emission intensity, we examine three potential mechanisms. Our results show that the decrease in trade policy uncertainty reduces emission intensity mainly by improving energy efficiency rather than improving abatement technology and optimizing energy structure. In addition, mainly for pollution-intensive and capital-intensive industries as well as coastal regions, the decrease in trade policy uncertainty helps to pollution reduction.

Altogether, we contribute to the literature in three primary aspects. First, we are the first to theoretically and empirically reveal how trade policy uncertainty affects firm-level pollution emissions. The literature examines the impact of trade policy on firms' environmental performance, which focuses on trade liberalization or tariff reduction. Cherniwchan (2017), Gutiérrez and Teshima (2018), Cui et al. (2020), and Liu et al. (2022) find that trade liberalization helps to reduce firms' pollution emissions. He et al. (2020b) give an opposite conclusion that trade liberalization aggravates pollution emissions.[1] However, these works are studied from the perspective of free trade or globalization. In the context of de-globalization and Sino-US trade friction, previous conclusions on trade liberalization cannot explain the environmental effect of trade policy uncertainty. It is necessary to study the relationship between trade policy and pollution emissions from the perspective of trade policy uncertainty. To reveal this relationship, we innovatively incorporate energy, pollution, and trade policy uncertainty into Melitz's (2003) framework.[2] We then employ Chinese data for empirical examination. Our conclusion reveals that trade policy uncertainty reduces emission intensity mainly by improving energy efficiency. In particular, we propose a theoretical mechanism that trade policy uncertainty reduces expected trade costs, which enables firms to invest more in upgrading production technology and thereby improve energy efficiency.[3] This finding is different from the literature that regards abatement technology as the mechanism by which trade reduces pollution emissions (Forslid et al. 2018; Rodrigue et al. 2022a; Kwon et al. 2023).

Second, we rely on an exogenous event that the USA granted PNTR to China to provide a novel evidence for the causal effect of exports on firm-level pollution emissions. The literature focuses on the relationship between firms' export behavior and environmental performance. These works provide evidences to support that exporting firms have better environmental performance relative to non-exporting firms (Roy and Yasar, 2015; Cui et al. 2016; Holladay, 2016; Banerjee et al. 2021; Kwon et al. 2023). Forslid et al. (2018), and He and Huang (2021) explain this relationship by constructing firm-level model based on Melitz's (2003) framework. Richter and Schiersch (2017) and Lin and He (2023a) indicate that firms with higher export intensity are cleaner. Barrows and Ollivier (2018) show the relationship between exporting product mix and environmental performance. Barrows and Ollivier (2021) find that foreign demand growth leads to export expansion, which aggravates emissions but reduces emission intensity. However, these works mainly employ export behavior as core variables. These variables are strongly endogenous due to self-selection effect (Melitz, 2003; Lin and He, 2023a), which is difficult to capture the causal effect of exports. Given that trade policy uncertainty is closely related to firms' export behavior (Pierce and Schott, 2016; Handley and Limão, 2017), the event that the USA granted PNTR to China provides an exogenous shock to identify the causal effect of exports.

Third, we contribute to the literature on the impact of trade policy uncertainty from an environmental perspective. The literature investigates micro-level impacts of trade policy uncertainty. Some works find that trade policy uncertainty hinders firms' exports (Handley, 2014; Handley and Limão, 2015, 2017; Feng et al. 2017). Other works show that this uncertainty affects labor employment (Pierce and Schott, 2016), investment (Pierce and Schott, 2016), and innovation (Liu and Ma, 2020). Handley and Limão (2017) provide an approach to introduce trade policy certainty into Melitz's (2003) model for theoretical analysis. As an important behavior of firms, firms' pollution emissions are closely related to the environmental quality of located region. Besides, pollution emissions are influenced by export behavior (Forslid et al. 2018), technical level (Shapiro and Walker, 2018), and output scale (Cherniwchan, 2017), implying that trade policy uncertainty is a potential factor affecting pollution emissions. In this study, we reveal a novel impact of trade policy uncertainty on firms' pollution emissions.

The remainder of this study is organized as follows. Section 2 provides a decomposition of firm-level pollution emissions. Section 3 constructs a theoretical model to analyze the environment effect of trade policy uncertainty. Section 4 introduces empirical strategy and data. Section 5 presents empirical results. Section 6 concludes.

2. A decomposition of firm-level pollution emissions

To reveal the potential mechanism by which trade policy uncertainty affects firms' pollution emissions, we propose a novel decomposition of pollution emissions. The literature focuses on the decomposition at macro-level (Grossman and Krueger, 1991; Antweiler et al. 2001). Different from these works, we decompose pollution emissions from the perspective of micro-firms. Our decomposition is also different from other firm-level decomposition (Cherniwchan et al. 2017).

First, the change in pollution emissions may be driven by the change in technology or output scale (Cherniwchan, 2017; Lin and He, 2023a). We decompose pollution emissions into emission intensity and output value, as shown in Eq. (1). Emission intensity is emission levels per unit of output value, reflecting the technology related to emissions. Firms with advanced technology have lower emission intensity, and they thereby emit less pollution under the condition of equal output value. Besides, output value is related to production scale. Under the condition of equal emission intensity, firms with larger scale inevitably have more pollution emissions.

$$Emissions = \underbrace{\frac{Emissions}{Output}}_{\text{Emission intensity}} \times \underbrace{Output}_{\text{Output value}} \tag{1}$$

Second, we decompose emission intensity to explore the channels of changing emission intensity. The technologies related to pollution emissions include production technology and abatement technology (Liu et al. 2021; Lin and He, 2023a, 2023b). We decompose emission intensity into the reciprocal of energy efficiency and abatement technology, as shown in equation (2). Energy efficiency is the output value per unit of energy consumption, reflecting the production technology related to energy input (Brucal et al. 2019; Huang et al. 2022). Firms with more advanced production technology have higher energy efficiency. They consume less energy per unit of output value and have lower emission intensity. Besides, abatement technology is emission levels per unit of energy consumption. Industrial emissions mainly come from energy consumption (Gutiérrez and Teshima, 2018). Firms with advanced abatement technology have stronger ability to terminally remove pollution (Liu et al. 2021). As a result, they emit less pollution per unit of energy consumption and have lower emission intensity (Lin and He, 2023a).

$$\underbrace{\frac{Emissions}{Output}}_{\text{Emission intensity}} = \underbrace{\frac{Energy}{Output}}_{\text{Reciprocal of energy efficiency}} \times \underbrace{\frac{Emissions}{Energy}}_{\text{Abatement technology (a)}} = \underbrace{\frac{Energy}{Output}}_{\text{Reciprocal of energy efficiency}} \times \underbrace{\frac{Emissions}{Coal}}_{\text{Abatement technology (b)}} \times \underbrace{\frac{Coal}{Energy}}_{\text{Energy structure}} \tag{2}$$

Third, emission levels per unit of energy consumption are influenced by energy structure. More emissions are from coal consumption, and other energies (such as fuel oil and clean gas) are cleaner. We decompose abatement technology into emission levels per unit of coal consumption and energy structure, as shown in equation (2). Emission levels per unit of coal consumption are related to abatement technology. Firms with advanced abatement technology have fewer emissions per unit of coal consumption and lower emission intensity (Liu et al. 2021). Besides, energy structure is the ratio of coal consumption to total energy consumption, reflecting the proportion of dirty energy. Firms consuming coals have higher emission intensity.

We employ the dataset merged by the Chinese Environmental Statistics Firm Database (CESFD) and the Chinese Industrial Firm Database (CIFD) to decompose the pollution emissions of Chinese firms. We employ sulfur dioxide (SO_2) as the pollutant to calculate the change rates of pollution emissions and decomposed variables relative to the baseline year (1998), as shown in Figure 1. The left panel shows that on average, firms' pollution emissions are fluctuating. Output scale keeps increasing, while emission intensity shows a downward trend. In addition, the

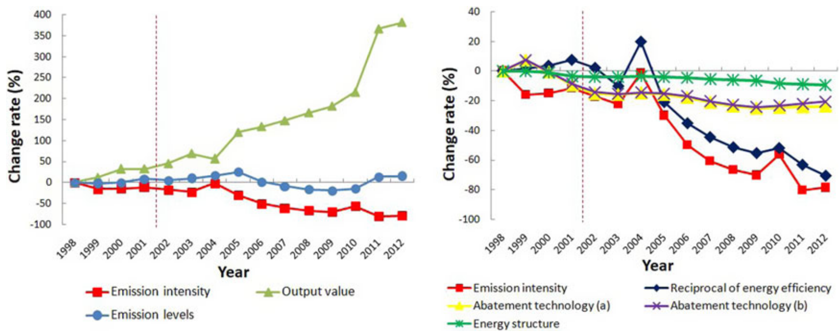

Figure 1. The change rates of pollution emission and decomposed variables of industrial firms in China, 1998-2012. Data sources: Calculation by the data from the Chinese Environmental Statistics Firm Database (CESFD) and the Chinese Industrial Firm Database (CIFD). Note: We employ SO_2 as the pollutant and 1998 as the baseline year. We delete the extreme values ranking in the top and bottom 1%.

right panel shows that the decrease of emission intensity is driven by increasing energy efficiency, improving abatement technology, and optimizing energy structure. In particular, the increase in energy efficiency makes the greatest contribution. The changes of energy efficiency and emission intensity show similar trends (especially after 2002).

From this Figure, there are two findings. The first one suggests that after 2001, Chinese firms expanded output scale and reduced emission intensity. This may be due to the decrease in trade policy uncertainty. The literature supports that Chinese firms expand output and reduce emission intensity after 2001, but these works focus on the impact of trade liberalization rather than trade policy uncertainty (Brandt et al. 2017; Cui et al. 2020). The second finding is that the change in emission intensity is mainly driven by the channel of energy efficiency. This is similar to Gutiérrez and Teshima (2018), that is, firms in developing countries mainly reduce emissions by improving energy efficiency. Thus, we focus on employing energy efficiency as a mechanism to analyze the impact of trade policy uncertainty on pollution emissions.

3. Theoretical model

3.1. Model setup

Our major setup is based on Melitz's (2003) model. We assume that there are two countries (home and foreign countries). Each country consists of a monopolistic competitive industry. Firms have heterogeneous production technologies (i.e. productivity). Each firm produces a product under increasing returns to scale. Different from Melitz's (2003) model, firms use labor and energy as production factors. Energy consumption produces pollution as by-products. Due to environmental regulation, firms need to pay for pollution emissions, such as pollution tax. To simplify this analysis, we assume that the stringency of environmental regulation is fixed.

3.1.1. Demand

For two countries, the utility function of representative consumers is standard constant elasticity of substitution (CES) form.

$$U = \left[\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where U is the utility of representative consumers. $q(\omega)$ is the demand of product variety ω, and Ω denotes the set of product variety. σ is the substitution elasticity among different varieties. $\rho = \frac{\sigma-1}{\sigma}$, $\sigma > 1$ and $0 < \rho < 1$.

Then, we calculate the demands of products in domestic and foreign markets.

$$q_h = \frac{R_h P_h^{\sigma-1}}{(p_h)^{\sigma}} \tag{4}$$

$$q_x = \frac{R_x P_x^{\sigma-1}}{(p_x)^{\sigma}} \tag{5}$$

where q_h and q_x are the demands of products in domestic and export markets. p_h and p_x are the prices of products in domestic and export markets. P_h and P_x are aggregate price indexes in domestic and export markets. R_h and R_x are aggregate expenditure indexes in domestic and export markets.

3.1.2. Production

We assume that firms employ labor and energy in production. Firms' productivity (φ) comes from a distribution function $G(\varphi)$ which is subject to the Pareto distribution. After paying fixed cost (f) to enter the industry, firms randomly draw their productivity from $G(\varphi)$. The initial productivity of firms is heterogeneous and exogenous. Firms can upgrade production technology (such as independent innovation and purchasing production equipment) to improve productivity. Investing in production technology requires payment of fixed costs (Bustos, 2011). Each firm decides the optimal investment for production technology according to own profit.

The production function is Cobb-Douglas form, including two kinds of production factors (energy and labor). We incorporate production technology investment referring to Bustos (2011).

$$q = h\left(f_R\right)\varphi e^{\alpha} l^{1-\alpha} \tag{6}$$

where q is firms' output. e and l are the levels of energy consumption and labor employment. α and $1-\alpha$ are the shares in energy and labor inputs. f_R represents the investment in production technology. According to Bustos (2011), if firms want to upgrade production technology, they need to pay fixed costs. $h\left(f_R\right)$ is the function for effect of production technology investment. $h'\left(f_R\right) > 0$ and $h(0) = 1$. When firms invest more in production technology, they gain higher productivity. The marginal effect of production technology investment on profit decreases progressively.[4]

We assume that the wage of labor employment is w ($w = 1$) and the price of energy consumption is P_e. Firms' optimal choice of labor employment and energy consumption is based on the prices of production factors. Namely, the marginal rate of technical substitution is equal to the ratio of wage to energy price ($MRTS = \frac{\frac{\partial q}{\partial l}}{\frac{\partial q}{\partial e}} = \frac{1}{P_e}$). By calculations, firms' labor employment and energy consumption are as follows:

$$l = \frac{q}{h\left(f_R\right)\varphi}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha} {P_e}^{\alpha} \tag{7}$$

$$e = \frac{q}{h\left(f_R\right)\varphi}\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} {P_e}^{\alpha-1} \tag{8}$$

We calculate firms' energy efficiency by the ratio of output to energy consumption.

$$\varphi_e = \frac{q}{e} = h\left(f_R\right)\varphi\left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} {P_e}^{1-\alpha} \tag{9}$$

where φ_e is firms' energy efficiency.

Energy consumption produces pollution as by-products. Firms' emission intensity and emission levels are as follows:

$$\gamma = \frac{z}{q} = \frac{z}{e} \times \frac{e}{q} = \frac{\theta}{h\left(f_R\right)\varphi}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1} \tag{10}$$

$$z = \frac{z}{q} \times q = \frac{\theta q}{h\left(f_R\right)\varphi}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1} \tag{11}$$

where γ and z are emission intensity and emission levels. θ is the emission levels per unit of energy consumption, which reflects abatement technology introduced in Section 2.

Firms not only pay fixed costs for production and production technology investment but also pay variable costs for labor and energy. Due to environmental regulation, firms need to pay for pollution emissions. The total cost function of production (or domestic sales) is as follows:

$$TC_h = f + f_R + eP_e + l + zP_z = f + f_R + \frac{q_h k}{h\left(f_R\right)\varphi} \tag{12}$$

where TC_h is the total cost of domestic sales. P_z is the cost per unit of pollution emissions. $k = \left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1}\left(\frac{P_e}{\alpha} + \theta P_z\right)$.

If firms export to foreign markets, they need to pay additional fixed cost and iceberg cost. The total cost function of exporting is as follows:

$$TC_x = f + f_R + f_x + \tau eP_e + \tau l + \tau zP_z = f + f_R + f_x + \frac{\tau q_x k}{h\left(f_R\right)\varphi} \tag{13}$$

where TC_x is the total cost of exporting. f_x is the fixed cost of exporting. τ is iceberg cost, such as tariff.[5] To simplify the theoretical analysis, we use tariff to represent iceberg cost.

Referring to Handley and Limão (2017), we design a simple way to introduce trade policy uncertainty. When there is no trade policy uncertainty in foreign country, foreign country imposes a lower tariff t. Iceberg cost is $\tau = 1 + t$. When there is a trade policy uncertainty, foreign country has a probability δ $(0 < \delta < 1)$ to impose a higher tariff $(t + \triangle t)$. Foreign country still has a probability $(1 - \delta)$ to impose a lower tariff t. That is to say, δ represents the existence of trade policy uncertainty. In addition, $\triangle t$ is the difference between higher and lower tariffs. Following Pierce and Schott (2016), we use $\triangle t$ to represent the degree of trade policy uncertainty. $\triangle t$ is larger, meaning that firms face a higher potential tariff rate. As a result, these firms are influenced by a higher degree of trade policy uncertainty.[6] In this case, the expected iceberg cost is as follows:

$$\tau' = \delta\left(t + \triangle t\right) + \left(1 - \delta\right)t + 1 \tag{14}$$

where $\tau' > \tau$ and $\frac{\partial \tau'}{\partial \triangle t} > 0$. When there is a trade policy uncertainty, the expected iceberg cost would be higher. Facing trade policy uncertainty, the total cost function of exporting is as follows:

$${TC_x}' = f + f_R + f_x + \tau' eP_e + \tau' l + \tau' zP_z = f + f_R + f_x + \frac{\tau' {q_x}' k}{h\left(f_R\right)\varphi} \tag{15}$$

where ${TC_x}'$ is the total cost of exporting in the presence of trade policy uncertainty. We further calculate marginal costs. $MC_h = \frac{k}{h(f_R)\varphi}$ is the marginal cost of domestic sales. $MC_x = \frac{\tau k}{h(f_R)\varphi}$ and ${MC_x}' = \frac{\tau' k}{h(f_R)\varphi}$ are marginal costs of exporting without and with trade policy uncertainty.

3.2. Firm behavior

According to monopolistic competitive industry and the CES utility function of consumers, firms set the profit-maximizing price by a constant markup over marginal cost. We calculate optimal prices of firms' products in domestic and foreign markets. $p_h = \frac{k}{\rho h(f_R)\varphi}$ is the price of domestic sales. $p_x = \frac{\tau k}{\rho h(f_R)\varphi}$ and $p_x{}' = \frac{\tau' k}{\rho h(f_R)\varphi}$ are the prices of exporting without and with trade policy uncertainty. We further calculate the volume of sales in domestic and export markets. $q_h = R_h P_h{}^{\sigma-1}\left[\frac{\rho h(f_R)\varphi}{k}\right]^{\sigma}$ is the volume of domestic sales. $q_x = R_x P_x{}^{\sigma-1}\left[\frac{\rho h(f_R)\varphi}{\tau k}\right]^{\sigma}$ and $q_x{}' = R_x P_x{}^{\sigma-1}\left[\frac{\rho h(f_R)\varphi}{\tau' k}\right]^{\sigma}$ are volumes of exports without and with trade policy uncertainty.

We calculate the profit functions of domestic sales and exporting. In particular, exporting firms serve both domestic and foreign markets, which is consistent with Melitz (2003).

$$\pi_h = B_h\left[h\left(f_R\right)\varphi\right]^{\sigma-1} - f - f_R \tag{16}$$

$$\pi_x = \left(B_h + B_x\tau^{1-\sigma}\right)\left[h\left(f_R\right)\varphi\right]^{\sigma-1} - f - f_R - f_x \tag{17}$$

$$\pi_x{}' = \left(B_h + B_x\tau'^{1-\sigma}\right)\left[h\left(f_R\right)\varphi\right]^{\sigma-1} - f - f_R - f_x \tag{18}$$

where π_h is the profit of domestic sales. $B_h = \frac{R_h P_h{}^{\sigma-1}\rho^{\sigma-1}}{\sigma k^{\sigma-1}}$. The profit of firms which sell in the domestic market is not influenced by trade policy uncertainty. In subsequent analysis, we focus on exporting firms.[7] π_x and $\pi_x{}'$ are the profits of exporting firms without and with trade policy uncertainty. $B_x = \frac{R_x P_x{}^{\sigma-1}\rho^{\sigma-1}}{\sigma k^{\sigma-1}}$. These profits are earned from domestic and export markets.

To simply solve the model, we assume the specific form of the function for production technology investment, that is $h\left(f_R\right) = \left(1+f_R\right)^{\frac{b}{\sigma-1}}$. This function meets $h'\left(f_R\right) > 0$ and $h(0) = 1$. Due to that the marginal effect of production technology investment on firm profit is decreasing ($\frac{\partial^2\pi}{\partial\left(f_R\right)^2} < 0$), we get $0 < b < 1$. For Eqs. (17) and (18), according to the condition of profit maximization ($\frac{\partial\pi}{\partial f_R} = 0$), we calculate the optimal levels of production technology investment.

$$f_{Rx} = \left(B_h + B_x\tau^{1-\sigma}\right)^{\frac{1}{1-b}}\varphi^{\frac{\sigma-1}{1-b}}b^{\frac{1}{1-b}} - 1 \tag{19}$$

$$f_{Rx}{}' = \left(B_h + B_x\tau'^{1-\sigma}\right)^{\frac{1}{1-b}}\varphi^{\frac{\sigma-1}{1-b}}b^{\frac{1}{1-b}} - 1 \tag{20}$$

where f_{Rx} and $f_{Rx}{}'$ are optimal levels of production technology investment for exporting firms without and with trade policy uncertainty. Since $\tau < \tau'$, we get $f_{Rx} > f_{Rx}{}'$. When there is a trade policy uncertainty, firms invest less in their production technology. This is because exporting firms may be subject to a higher expected tariff in the presence of trade policy uncertainty, and expected iceberg cost faced by firms is also higher. As a result, they reduce the cost for production technology investment.

Furthermore, we put Eq. (14) into Eq. (20) and calculate the partial derivative of $\triangle t$.

$$\frac{\partial f_{Rx}{}'}{\partial\triangle t} = \frac{1-\sigma}{1-b}B_x\delta\tau'^{-\sigma}\left(B_h + B_x\tau'^{1-\sigma}\right)^{\frac{b}{1-b}}\varphi^{\frac{\sigma-1}{1-b}}b^{\frac{1}{1-b}} < 0 \tag{21}$$

From Eq. (21), the increase in trade policy uncertainty reduces production technology investment. Conversely, the decrease in trade policy uncertainty helps to upgrade production technology. The reason is that the decrease in trade policy uncertainty reduces expected iceberg cost, making exporting firms invest more in production technology.

3.3. Energy efficiency and pollution emissions

We put $h\left(f_R\right) = \left(1 + f_R\right)^{\frac{b}{\sigma-1}}$ as well as equations (19) and (20) into equation (9) to calculate the energy efficiency of exporting firms.

$$\varphi_{ex} = \left(1 + f_{Rx}\right)^{\frac{b}{\sigma-1}} \varphi \left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} {P_e}^{1-\alpha} \tag{22}$$

$$\varphi_{ex}{}' = \left(1 + f_{Rx}{}'\right)^{\frac{b}{\sigma-1}} \varphi \left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} {P_e}^{1-\alpha} \tag{23}$$

where φ_{ex} and $\varphi_{ex}{}'$ are the energy efficiency of exporting firms without and with trade policy uncertainty. Since $f_{Rx} > f_{Rx}{}'$, we get $\varphi_{ex} > \varphi_{ex}{}'$. When there is a trade policy uncertainty, exporting firms reduce energy efficiency. The reason is that if exporting firms face trade policy uncertainty, they would be influenced by higher expected iceberg cost and reduce production technology investment. This reduction in production technology investment leads to lower energy efficiency.

In addition, we analyze the impact of change in trade policy uncertainty ($\triangle t$) on firm-level energy efficiency. For equation (23), we calculate the partial derivative of $\triangle t$.

$$\frac{\partial \varphi_{ex}{}'}{\partial \triangle t} = \frac{b}{\sigma - 1} \left(1 + f_{Rx}{}'\right)^{\frac{b-\sigma+1}{\sigma-1}} \frac{\partial f_{Rx}{}'}{\partial \triangle t} \varphi \left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} {P_e}^{1-\alpha} < 0 \tag{24}$$

Given that the increase in trade policy uncertainty reduces production technology investment ($\frac{\partial f_{Rx}{}'}{\partial \triangle t} < 0$), we get $\frac{\partial \varphi_{ex}{}'}{\partial \triangle t} < 0$. This result suggests that the increase in trade policy uncertainty reduces exporting firms' energy efficiency. Conversely, the decrease in trade policy uncertainty is conducive to improving energy efficiency. This improvement of energy efficiency is driven by decreasing expected iceberg cost and thereby upgrading production technology.

Then, we put $h\left(f_R\right) = \left(1 + f_R\right)^{\frac{b}{\sigma-1}}$ as well as equations (19) and (20) into equation (10) to calculate the emission intensity of exporting firms.

$$\gamma_x = \frac{\theta}{\varphi} \left(1 + f_{Rx}\right)^{\frac{b}{1-\sigma}} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1} \tag{25}$$

$$\gamma_x{}' = \frac{\theta}{\varphi} \left(1 + f_{Rx}{}'\right)^{\frac{b}{1-\sigma}} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1} \tag{26}$$

where γ_x and $\gamma_x{}'$ are the emission intensity of exporting firms without and with trade policy uncertainty. Since $f_{Rx} > f_{Rx}{}'$ and $\frac{b}{1-\sigma} < 0$, we get $\gamma_x < \gamma_x{}'$. Exporting firms increase emission intensity in the presence of trade policy uncertainty. The reason is that when there is a trade policy uncertainty, exporting firms reduce production technology investment due to the increase in expected cost and thereby reduce energy efficiency. This leads to higher emission intensity.

Also, we analyze the impact of change in trade policy uncertainty ($\triangle t$) on emission intensity. We calculate the partial derivative of $\triangle t$ for equation (26).

$$\frac{\partial \gamma_x{}'}{\partial \triangle t} = \frac{\theta}{\varphi} \left(\frac{b}{1-\sigma}\right) \left(1 + f_{Rx}{}'\right)^{\frac{b+\sigma-1}{1-\sigma}} \frac{\partial f_{Rx}{}'}{\partial \triangle t} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} {P_e}^{\alpha-1} > 0 \tag{27}$$

Since $\frac{\partial f_{Rx}{}'}{\partial \triangle t} < 0$ and $\frac{b}{1-\sigma} < 0$, we get $\frac{\partial \gamma_x{}'}{\partial \triangle t} > 0$. This result indicates that the increase in trade policy uncertainty increases emission intensity. On the contrary, the decrease in trade policy uncertainty reduces emission intensity. The theoretical mechanism is that the decrease in trade policy uncertainty reduces expected trade cost faced by exporting firms, leading to more investments in production technology and thereby improving energy efficiency. It can help to reduce emission intensity of exporting firms. This implies the following proposition:

Proposition 1. *The decrease in trade policy uncertainty reduces emission intensity of exporting firms.*

Next, emission levels are the product of emission intensity and output. We put $h\left(f_R\right) = \left(1+f_R\right)^{\frac{b}{\sigma-1}}$ as well as equations (19) and (20) into q_h, q_x, and $q_x{}'$ to calculate the volumes of domestic sales and exports. It is noted that exporting firms' output includes domestic sales and exports.

$$q_h + q_x = RP^{\sigma-1}\left[\frac{\rho\varphi}{k}\right]^{\sigma}\left(1+f_R\right)^{\frac{\sigma b}{1-\sigma}}\left(1+\frac{1}{\tau^{\sigma}}\right) \tag{28}$$

$$q_h + q_x{}' = RP^{\sigma-1}\left[\frac{\rho\varphi}{k}\right]^{\sigma}\left(1+f_R{}'\right)^{\frac{\sigma b}{1-\sigma}}\left(1+\frac{1}{\tau'^{\sigma}}\right) \tag{29}$$

where $\left(q_h+q_x\right)$ and $\left(q_h+q_x{}'\right)$ are the outputs of exporting firms without and with trade policy uncertainty. Since $f_{Rx} > f_{Rx}{}'$ and $\tau < \tau'$, we get $q_h + q_x > q_h + q_x{}'$. Exporting firms reduce output scale in the presence of trade policy uncertainty. The explanation is that when there is a trade policy uncertainty, exporting firms face higher iceberg cost and reduce production technology investment. As a result, their output scale would be decreased.

We further analyze the impact of change in trade policy uncertainty ($\triangle t$) on output scale. For equation (29), we calculate the partial derivative of $\triangle t$.

$$\begin{aligned}\frac{\partial\left(q_h+q_x{}'\right)}{\partial\triangle t} = RP^{\sigma-1}\left(\frac{\rho\varphi}{k}\right)^{\sigma}\Bigg[\frac{\sigma b}{1-\sigma}\left(1+f_R{}'\right)^{\frac{\sigma(b+1)-1}{1-\sigma}}\frac{\partial f_{Rx}{}'}{\partial\triangle t}\left(1+\frac{1}{\tau'^{\sigma}}\right)\\ -\left(1+f_R{}'\right)^{\frac{\sigma b}{1-\sigma}}\frac{\sigma}{\tau'^{\sigma+1}}\frac{\partial\tau'}{\partial\triangle t}\Bigg] < 0\end{aligned} \tag{30}$$

Since $\frac{\partial f_{Rx}{}'}{\partial\triangle t} < 0$ and $\frac{\partial\tau'}{\partial\triangle t} > 0$, we get $\frac{\partial\left(q_h+q_x{}'\right)}{\partial\triangle t} < 0$. Namely, the increase in trade policy uncertainty reduces output scale. Conversely, if exporting firms face less trade policy uncertainty, they expand output scale. The explanation is that the decrease in trade policy uncertainty leads to more investments in production technology and decrease in expected trade cost, which helps to expanding output of exporting firms.

We put $h\left(f_R\right) = \left(1+f_R\right)^{\frac{b}{\sigma-1}}$ as well as equations (19), (20), (28), and (29) into equation. (11) to calculate the emission levels of exporting firms.

$$z_x = \frac{\theta\left(q_h+q_x\right)}{\varphi}\left(1+f_{Rx}\right)^{\frac{b}{1-\sigma}}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1}P_e{}^{\alpha-1} \tag{31}$$

$$z_x{}' = \frac{\theta\left(q_h+q_x{}'\right)}{\varphi}\left(1+f_{Rx}{}'\right)^{\frac{b}{1-\sigma}}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1}P_e{}^{\alpha-1} \tag{32}$$

where z_x and $z_x{}'$ are emission levels of exporting firms without and with trade policy uncertainty. Based on above analyses, $f_{Rx} > f_{Rx}{}'$, $\frac{b}{1-\sigma} < 0$ and $q_h + q_x > q_h + q_x{}'$. Thus, the relative sizes of z_x and $z_x{}'$ are uncertain. Namely, when exporting firms face trade policy uncertainty, it is uncertain whether they increase or reduce emission levels. The reason is that on the one hand, trade policy uncertainty leads to increasing emission intensity; on the other hand, trade policy uncertainty reduces output scale. Smaller firms have lower emission levels, while firms with higher emission intensity have higher emission levels. As a result, the impact of trade policy uncertainty on emission levels is uncertain.

We continue to analyze the impact of change in trade policy uncertainty ($\triangle t$) on emission levels. For equation (32), we calculate the partial derivative of $\triangle t$.

$$\frac{\partial z_x{}'}{\partial \triangle t} = \frac{\theta}{\varphi}\left(\frac{1-\alpha}{\alpha}\right)^{\alpha-1} P_e{}^{\alpha-1}\left[\frac{\partial\left(q_h+q_x{}'\right)}{\partial \triangle t}\left(1+f_R{}'\right)^{\frac{b}{1-\sigma}} + \left(q_h+q_x{}'\right)\frac{b}{1-\sigma}\left(1+f_R{}'\right)^{\frac{b+\sigma-1}{1-\sigma}}\frac{\partial f_{Rx}{}'}{\partial \triangle t}\right] \tag{33}$$

From above analyses, $\frac{\partial\left(q_h+q_x{}'\right)}{\partial\triangle t} < 0$, $\frac{\partial f_{Rx}{}'}{\partial\triangle t} < 0$, and $\frac{b}{1-\sigma} < 0$. It is uncertain that $\frac{\partial z_x{}'}{\partial\triangle t}$ is greater or less than 0. The impacts of changing trade policy uncertainty are uncertain. This is because the decrease in trade policy uncertainty not only reduces emission intensity but also expands output scale. Both emission intensity and output scale are correlated with emission levels.

Given that emission levels are the product of emission intensity and output, that is $z_x{}' = \gamma_x{}'\left(q_h+q_x{}'\right)$, we calculate the partial derivative of $\triangle t$.

$$\frac{\partial z_x{}'}{\partial \triangle t} = \underbrace{\frac{\partial \gamma_x{}'}{\partial \triangle t}\left(q_h+q_x{}'\right)}_{>0} + \underbrace{\frac{\partial\left(q_h+q_x{}'\right)}{\partial \triangle t}\gamma_x{}'}_{<0} \tag{34}$$

Equation (34) also suggests that the decrease in trade policy uncertainty reduces emission intensity and expands output scale. The impact of trade policy uncertainty on emission levels depends on the relative sizes of these two channels. This implies the following proposition:

Proposition 2. *The impact of decrease in trade policy uncertainty on emission levels of exporting firms is uncertain, which depends on the relative changes in emission intensity and output scale.*

Finally, emission intensity can be decomposed into energy efficiency and abatement technology, that is $\gamma = \frac{\theta}{\varphi_e}$. From above analyses, improving energy efficiency can reduce firms' emission intensity, that is $\frac{\partial\gamma}{\partial\varphi_e} < 0$. The decrease in trade policy uncertainty increases production technology investment and thereby improves energy efficiency, that is $\frac{\partial\varphi_{ex}{}'}{\partial\triangle t} < 0$.

$$\frac{\partial \gamma_x{}'}{\partial \triangle t} = \underbrace{\frac{\partial \gamma_x{}'}{\partial \varphi_{ex}{}'}}_{<0} \times \underbrace{\frac{\partial \varphi_{ex}{}'}{\partial \triangle t}}_{<0} > 0 \tag{35}$$

This equation indicates that the decrease in trade policy uncertainty reduces exporting firms' emission intensity by the mechanism of upgrading production technology and thereby improving energy efficiency. This implies the following proposition:

Proposition 3. *Improving energy efficiency is an important mechanism by which the decrease in trade policy uncertainty reduces emission intensity of exporting firms.*

4. Empirical strategy and data

4.1. Identifying the impact of trade policy uncertainty

Our theoretical model has predicted the potential relationship between trade policy uncertainty and firms' pollution emissions. We employ the data of Chinese manufacturing firms to examine this relationship. We follow Pierce and Schott (2016) and regard the permanent normal trade relationship (PNTR) granted to China by the USA in 2002 as a quasi natural experiment. This event has been adopted by other literature to identify the causal effect of trade policy uncertainty (Handley and Limão, 2017; Feng et al. 2017; Pierce and Schott, 2018; Liu and Ma, 2020). We construct a DDD model to analyze the impact of trade policy uncertainty on pollution emissions. We introduce the background of this event and the measurement of industry-level trade policy uncertainty as follows.

4.1.1. Event background

Before China's entry into the WTO, the USA granted temporary normal trade relationship to China. The US Congress annually voted on whether to grant normal trade relationship to China. If China was granted normal trade relationship, the USA imposed MFN tariff (with lower tariff rate) on Chinese products. Otherwise, the USA imposed column 2 tariff (with higher tariff rate). The column 2 tariff originated from the Smoot-Hawley Tariff Act in 1930. This tariff is applicable to countries that do not establish normal trade relationship with the USA. This tariff rate is much higher relative to MFN tariff. In other words, it was uncertain whether the USA granted MFN tariff to China every year. According to Pierce and Schott (2016), from 1990 to 1992, the USA continuously refused to grant MFN tariff to China; from 1990 to 2001, the proportion of negative votes is approximately 39%. Taking 2000 as an example, if China failed to be granted MFN tariff, the average tariff rate would be increased from 7% to 31%. We can see that before the USA granted PNTR to China, Chinese firms faced a higher degree of trade policy uncertainty.

After China's entry into the WTO, the USA granted PNTR to China on January 1, 2002. Since then, the USA granted MFN tariff to China every year. China's external trade policy uncertainty significantly decreases. Benefiting from this event, the number of Chinese exporting firms rapidly increases, and firms' export scale expands (Feng et al. 2017). Based on this background, the event that the USA granted PNTR to China in 2002 provides a quasi natural experiment for identifying the causal effect of changing trade policy uncertainty.

According to Pierce and Schott (2016), before the USA granted PNTR to China in 2002, the differences in tariff rates between column 2 tariff and MFN tariff for various industries were different. The industries with greater difference in tariff rates experienced greater decrease in trade policy uncertainty after this event. The reason is that if there is a greater difference between two types of tariffs for a given industry, firms would potentially face a higher expected trade cost before the USA granted PNTR to China. After the USA granted PNTR to China, trade policy uncertainty would decrease to a greater extent. On the contrary, if there is only a smaller difference between two types of tariffs for a given industry, the expected trade cost would not decrease too much after the USA granted PNTR to China. Therefore, we can employ the difference between column 2 tariff and MFN tariff for various industries in China before the USA granted PNTR to China to measure the decrease in trade policy uncertainty at the industry level.[8] In addition, column 2 tariff originates from the Smoot-Hawley Tariff Act in 1930, which is strongly exogenous (Pierce and Schott, 2016).

4.1.2. The measurement of trade policy uncertainty

We follow Pierce and Schott (2016) to measure trade policy uncertainty for various industries in China. The measurement is divided into two steps. The first step is to calculate product-level trade policy uncertainty using the data provided by Feenstra et al. (2002).

$$TPU_k = Tariff_k^{Col2} - Tariff_k^{MFN} \tag{36}$$

where subscript k denotes product. TPU_k is trade policy uncertainty of k product before the USA granted PNTR to China in 2002. $Tariff_k^{Col2}$ and $Tariff_k^{MFN}$ are the tariff rates of column 2 tariff and MFN tariff imposed by the USA.

The second step is to aggregate product-level trade policy uncertainty at the industry level. Then, we can obtain trade policy uncertainty for each industry in China.

$$TPU_s = \frac{\sum_{k\in I_s} n_k TPU_k}{\sum_{k\in I_s}^{n_k}} \tag{37}$$

where subscript s denotes industry. TPU_s is trade policy uncertainty of s industry before the USA granted PNTR to China. n_k is the number of tariff items of k product. I_s is the product set of

s industry. The value of TPU_s is greater, meaning that the degree of industry-level trade policy uncertainty before 2002 is higher. After the USA granted PNTR to China in 2002, this industry experienced a greater decrease in trade policy uncertainty.

4.2. Empirical model

Our theoretical section focuses on exporting firms. Compared with firms selling in the domestic market, trade policy uncertainty is more likely to affect exporting firms' pollution emissions. In addition, the PNTR granted to China refers to the trade policy of USA. Many Chinese exporters regard the USA as a major export destination. This event shock has a greater impact on firms exporting to the USA. Thus, we construct a DDD model to empirically investigate the impact of decrease in trade policy uncertainty on firms' pollution emissions.

$$\ln Y_{ispt} = \beta_1 TPU_s \times Post_t \times USEX_{ispt} + \beta_2 TPU_s \times USEX_{ispt} + \beta_3 Post_t \times USEX_{ispt} \\ + \beta_4 USEX_{ispt} + X'\theta + \mu_{st} + \delta_{pt} + \varepsilon_{ispt} \tag{38}$$

where subscripts i, s, p, and t denote individual firm, industry, province, and time, respectively. Y_{ispt} includes firms' emission intensity, output value, and emission levels. We employ SO_2 as the pollutant. TPU_s represents the degree of trade policy uncertainty of s industry before the USA granted PNTR to China in 2002. $Post_t$ is a time-level dummy before and after 2002. If a firm is in the period of 2002 or after 2002, $Post_t = 1$; otherwise, $Post_t = 0$. $USEX_{ispt}$ is a dummy of exporting to the USA. If a firm exports to the USA, $USEX_{ispt} = 1$; otherwise, $USEX_{ispt} = 0$. The triple interaction term $TPU_s \times Post_t \times USEX_{ispt}$ is the core variable. We focus on β_1, which measures the impacts of decrease in trade policy uncertainty on firms' emission intensity, output value, and emission levels on average. X' is control variables at the firm level, including capital intensity ($\ln KL_{ispt}$), financing constraint ($\ln Constraint_{ispt}$) and ownership types (SOE_{ispt} and $Foreign_{ispt}$).[9] μ_{st} is industry-year fixed effect, which captures industry-level characteristics, policies, and shocks. For example, tariff changes are reflected at the industry-time level, which affects firms' environmental performance (Cherniwchan, 2017; Gutiérrez and Teshima, 2018). δ_{pt} is province-year fixed effect, which captures region-level characteristics, policies, and shocks. For example, environmental regulation is usually reflected at region-time level in China (Shi and Xu, 2018).[10] ε_{ispt} is a stochastic error term.

Next, we discuss the endogeneity of core variable ($TPU_s \times Post_t \times USEX_{ispt}$) in Eq. (38). TPU_s is the degree of trade policy uncertainty which is measured by column 2 tariff and MFN tariff imposed by the USA. Column 2 tariff comes from the Smoot-Hawley Tariff Act in 1930, which is strongly exogenous (Pierce and Schott, 2016; Feng et al. 2017; Liu and Ma, 2020). $Post_t$ is an exogenous dummy to distinguish periods. However, $USEX_{ispt}$ is an endogenous dummy of whether firms export to the USA. First, there are omitted factors that may affect exporting and environmental performance (Lin and He, 2023a). Second, there may be a reverse causal relationship between export behavior and environmental performance. Namely, firms with better environmental performance may self-select to export to the USA (Lin and He, 2023a). Third, the change in trade policy uncertainty significantly affects firms' export behavior (Handley and Limão, 2017; Feng et al. 2017). As a consequence, the coefficient on core variable may confound the impact of trade policy uncertainty on export behavior.

To address the endogeneity of exporting to the USA, we construct instrumental variables (IV). IV needs to meet the conditions of exogeneity and correlation. We refer to Frankel and Rose (2005) and Lin (2017) and employ the distance between the located city of firms and the nearest port[11] as IV of exporting to the USA. On the one hand, the distance between located city and port is relatively exogenous, which is difficult to directly affect firms' pollution emissions. On the other hand, this IV is closely correlated with firms' export behavior. The majority of exports from China to the USA rely on ocean shipping. If firms are closer to the port, these firms have more possibilities to sell products to the USA.

In addition, the distance from the port is a region-level variable. It can only capture region-level variation in firms' export behavior. The variation in export behavior also reflects at the time level. Referring to Bastos et al., (2018), the exchange rate of US dollar to China Yuan[12] can be regarded as another IV. On the one hand, exchange rate is an exogenous variable. This variable mainly affects firms' pollution emissions through trade behavior. On the other hand, exchange rate is closely correlated with export behavior. If the exchange rate of US dollar to China Yuan increases, it would be more conducive for Chinese firms to export to the USA. Thus, we employ the interaction term of the distance from the port and exchange rate as IV.

4.3. Data

This study involves three firm-level databases of China. First, our data on firms' environmental performance are from the Chinese Environmental Statistics Firm Database (CESFD) provided by the Ministry of Ecology and Environment of China from 1998 to 2012. This database contains firm-level information on pollution emissions, energy consumption as well as abatement equipment and capacity. Since 1980, the Ministry of Ecology and Environment of China has established a system of environmental statistics to annually collect data on pollution emissions. This database covers the major industrial emitters monitored by the Ministry of Ecology and Environment. Their emission levels account for 85% of region-level emissions. Statistical items include major pollutants, such as SO_2 and chemical oxygen demand (COD). Monitored firms are required to report basic facts, output value, and a large amount of environmental information. In general, this database is a comprehensive, reliable, and authoritative firm-level environmental database in China (Liu et al. 2017; Zhang et al. 2018; He et al. 2020a).

Second, CESFD covers abundant environmental information, but it does not provide information on exporting and finance. To obtain more firm-level information, we employ the CIFD provided by the National Bureau of Statistics of China from 1998 to 2012. This database covers all state-owned firms and non-state-owned firms with large scale in China. This database provides basic facts about firms as well as information on production, exporting, and finance. According to our design and the method of data processing from Feenstra et al. (2014) and Yu (2015), we process the abnormal and missing data of this database. In particular, manufacturing firms are more likely to be influenced by trade policy uncertainty. We only retain firms from manufacturing industries. We remove any firms whose output value and the value of fixed asset are less than or equal to 0, any firms whose interest expenditure is less than 0, and any firms whose employees are less than 10. In addition, we deflate output value, export value, and interest expenditure by the industrial producer price index of 1998, and deflate the value of fixed asset by the fixed asset investment price index of 1998. Then, we use firm code, name, and former name to match this database with CESFD.

Third, we collect data to identify whether firms export to the USA. This information is from the Chinese Custom Database (CCD) provided by the General Administration of Customs of China from 2000 to 2012. This database records monthly transaction information on exports (including export destination). We sum up this data at the firm-year level. Following Dai et al. (2016), we match this database with the above dataset through firm name as well as the zip code plus the last seven digits of telephone number.

In addition, the data on column 2 tariff and MFN tariff imposed by the USA on China are from Feenstra et al. (2002). The literature uses this data to measure trade policy uncertainty faced by Chinese firms (Pierce and Schott, 2016, 2018; Feng et al. 2017; Liu and Ma, 2020). We match this industry-level trade policy uncertainty with firm-level databases.

After matching, we obtain a dataset of 644,122 observations, including 577,539 observations of manufacturing firms. This dataset contains information on trade policy uncertainty as well as firm-level environmental performance, export behavior, and other characteristics. There are 428,615 observations emitting SO_2, 427,227 observations emitting COD, 151,707 observations of exporters and 41,005 observations exporting to the USA, as shown in Table 1.

Table 1. The observations of merged dataset

	All firms	Firms emitting SO_2	Firms emitting COD
All observations	644,122	431,567	429,923
Observations of manufacturing firms	577,539	428,615	427,227
Observations of exporting firms	151,707	98,116	129,543
Observations of firms exporting to the USA	41,005	25,079	35,728

Table 2. The comparison between merged dataset and CESFD

Year	Merged dataset			CESFD			Matching rate
	Observation	Average SO_2 emission levels	Average COD emission levels	Observation	Average SO_2 emission levels	Average COD emission levels	
1998	26,111	447104.4	195051.4	55,855	298855.5	282697.1	46.75%
1999	30,329	318166.3	170825.4	65,282	218321.8	140638.8	46.46%
2000	32,563	328723	135451.4	70,223	234635.9	119782.6	46.37%
2001	31,912	337404.1	128646.7	70,187	250702.5	112684.3	45.47%
2002	32,081	346345.2	109489.9	68,191	254439.5	99,170.67	47.05%
2003	33,276	387856.3	108979.4	69,323	283651	96,217.51	48.00%
2004	38,363	421806.4	100046	70,457	333966.4	94,266.93	54.45%
2005	38,434	488424.9	110355.6	70,094	392809.2	103947.5	54.83%
2006	42,549	186047.4	98,828.31	76,501	162503.9	90,705.6	55.62%
2007	52,463	161460.8	76,252.29	104,059	118689.8	64,583.8	50.42%
2008	53,366	135590.5	63,682.75	108,598	110728	54,339.98	49.14%
2009	50,125	134841.3	55,134.85	109,149	109235.9	49,135.45	45.92%
2010	50,236	150397.7	55,136.55	111,127	112423.4	47,659.96	45.21%
2011	65,314	302872.7	41,386.06	153,031	185120.9	34,890.56	42.68%
2012	67,000	284789.2	39,599.89	147,938	181355.7	33,290.84	45.29%
Total	644,122	282990.7	86,017.7	1,350,015	199611.5	80,841.6	47.71%

Notes: Given that initial CESFD does not provide the industry type for each firm, this table shows the information on all industrial firms (including manufacturing firms and other industrial firms).

As suggested by He et al. (2020a), matching CESFD with other firm-level database may be problematic. We compare the merged dataset with initial CESFD in Table 2. First, there are 1,350,015 observations in initial CESFD and 644,122 observations in merged dataset. Approximately, 47.71% of observations are successfully matched. This matching rate is similar to Lin and He (2023a), which matches CESFD with CIFD and CCD from 1998 to 2012. Specifically, from 1998 to 2012, these matching rates are 42.68%-55.62%. The changes in observations of merged dataset and CESFD show similar trends. Second, in initial CESFD, average SO_2 and COD emission levels are 282990.7 and 86,017.7 kilograms. In merged dataset, they are 199611.5 and 80,841.6 kilograms. From 1998 to 2012, the change trends in average emission levels of merged dataset and CESFD are almost the same. Thus, after matching, firm-level environmental performance does not significantly change relative to initial CESFD. Our matched dataset is quite representative, which is suitable for empirical analysis.

Table 3 shows the descriptive statistics on main variables. Our dataset includes firms with more and less emissions, exporters and non-exporters, and firms with different characteristics. Besides, different firms face differentiated degrees of decreases in trade policy uncertainty.

Table 3. Descriptive statistics on main variables

Variable	Definition	Observation	Mean	Std. Dev.	Minimum	Maximum
EI_{ispt} (SO_2)	SO_2 emission intensity	428,615	1165.123	63,563.68	3.42E-08	2.40E + 07
E_{ispt} (SO_2)	SO_2 emission levels	428,615	162218.9	3549504	1	2.18E + 09
EI_{ispt} (COD)	COD emission intensity	427,227	701.551	109972.2	1.66E-08	6.98E + 07
E_{ispt} (COD)	COD emission levels	427,227	90,133.33	675662.6	0.1	7.53E + 07
$Output_{ispt}$	Output value	577,539	339906.2	2400354	1	2.20E + 08
TPU_s	The degree of trade policy uncertainty	577,539	0.1991	0.1239	0	0.4189
$Post_t$	Before and after 2002	577,539	0.8118	0.3909	0	1
$USEX_{ispt}$	Export to the USA or not	526,765	0.0776	0.2676	0	1
EX_{ispt}	Export or not	543,043	0.2782	0.4481	0	1
EXI_{ispt}	Export intensity	541,311	0.1178	0.2734	0	1
KL_{ispt}	Capital intensity	577,539	358.3119	8592.323	3.72E-05	2034872
$Constraint_{ispt}$	Financing constraint	577,539	19.6141	1818.987	3.37E-09	972227
SOE_{ispt}	State-owned firm or not	577,539	0.1231	0.3286	0	1
$Foreign_{ispt}$	Foreign-funded firm or not	577,539	0.1998	0.3998	0	1

5. Empirical results

5.1. Baseline results: 2SLS estimation

We employ Eq. (38) to examine the impact of trade policy uncertainty on firm-level pollution emissions, which refers to the Propositions 1 and 2 in the theoretical section. Specifically, we employ the interaction term of the distance from the port and exchange rate as IV. We use two-stage least square (2SLS) method for analysis. The panel A of Table 4 reports these results. The column (1) shows the result for the first stage of 2SLS estimation. The coefficient on IV ($\ln Distance_{ispt} \times Exchange_t$) is negative and significant at the 1% level. This result indicates that both the distance from the port and exchange rate of US dollar to China Yuan are negatively correlated with export behavior. If firms are closer to the port and US dollar can exchange more Chinese yuan, firms are more likely to export products to the USA. It proves that there is a significant correlation between IV and exporting to the USA. In addition, the F value is approximately 527.59, illustrating that this IV is not a weak IV.

Columns (2)-(7) show the results for the second stage. Dependent variables include emission intensity, output value, and emission levels. In columns (2) and (3), we examine the impact of decrease in trade policy uncertainty on firms' emission intensity. The coefficients on the triple interaction term ($TPU_s \times Post_t \times \widehat{USEX}_{ispt}$) are negative and significant at the 1% level. These results indicate that for firms which export to the USA, the decrease in trade policy uncertainty leads to lower emission intensity. These results support the Proposition 1. The explanation is that the decrease in trade policy uncertainty reduces expected trade cost. As a consequence, firms invest more in technical upgrading and thereby reduce emission intensity.

In columns (4) and (5), we analyze the impact of decrease in trade policy uncertainty on firms' output scale. The coefficients on $TPU_s \times Post_t \times \widehat{USEX}_{ispt}$ are positive and significant at the 1% level. These results suggest that for firms which export to the USA, the decrease in trade policy uncertainty leads to greater output value. Theoretical section explains that on the one hand, the decrease in trade policy uncertainty promotes technology investment and improves production capacity. On the other hand, the decrease in trade policy uncertainty directly expands export scale and then expands output.

According to Eq. (1), emission levels are decomposed into emission intensity and output value. Firms with lower emission intensity have lower emission levels, but firms with greater outputs have more emissions. Combining the results in columns (2)-(5), we cannot conclude that trade

Table 4. 2SLS estimation: the impact of trade policy uncertainty on pollution emissions

	The first stage	The second stage					
	Export to US	Emission intensity		Output value		Emission levels	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: The interaction term of distance from port and exchange rate as IV							
ln $Distance_{ispt} \times Exchange_t$	-0.0810^{***}						
	(0.0066)						
$TPU_s \times Post_t \times \widehat{USEX}_{ispt}$		-6.0458^{***}	-4.8999^{***}	6.9851^{***}	5.8416^{***}	0.5397	−0.1213
		(1.7864)	(1.7732)	(1.2090)	(1.1498)	(1.6403)	(1.6102)
$TPU_s \times \widehat{USEX}_{ispt}$		12.6048^{***}	11.5455^{***}	-12.3811^{***}	-12.7898^{***}	−0.3669	−0.7416
		(1.7574)	(1.7415)	(1.2774)	(1.2051)	(1.6441)	(1.6098)
$Post_t \times \widehat{USEX}_{ispt}$		2.5454^{***}	1.5832^{***}	-2.5334^{***}	-2.0008^{***}	0.3011	−0.2327
		(0.4601)	(0.4564)	(0.3146)	(0.3019)	(0.4299)	(0.4246)
$\widehat{USEX}_{ispt}$		-10.8902^{***}	-10.0727^{***}	9.7335^{***}	2.0077^{***}	-1.0808^{**}	-7.4841^{***}
		(0.4558)	(0.7245)	(0.3340)	(0.4949)	(0.4397)	(0.7287)
Firm characteristics	YES	NO	YES	NO	YES	NO	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES
Observation	525,170	384,635	384,635	525,170	525,170	384,635	384,635
Adjusted R^2	0.0899	0.3795	0.3848	0.3535	0.4148	0.1920	0.2183
F value	527.59						
Panel B: The interaction term of distance from port and exchange rate as IV (Removing firms with changing locations)							
ln $Distance_{ispt} \times Exchange_t$	-0.0800^{***}						
	(0.0066)						
$TPU_s \times Post_t \times \widehat{USEX}_{ispt}$		-6.7045^{***}	-5.5101^{***}	7.4609^{***}	6.3005^{***}	0.3238	−0.2691
		(1.7546)	(1.7394)	(1.2100)	(1.1492)	(1.6337)	(1.6040)
$TPU_s \times \widehat{USEX}_{ispt}$		13.0871^{***}	11.9597^{***}	-12.7823^{***}	-13.0754^{***}	−0.2247	−0.5804
		(1.7207)	(1.7029)	(1.2744)	(1.2014)	(1.6351)	(1.6013)
$Post_t \times \widehat{USEX}_{ispt}$		2.5732^{***}	1.6228^{***}	-2.5964^{***}	-2.0359^{***}	0.2867	−0.2191
		(0.4575)	(0.4534)	(0.3143)	(0.3010)	(0.4309)	(0.4259)
$\widehat{USEX}_{ispt}$		-10.8818^{***}	-9.9490^{***}	9.7759^{***}	2.1758^{***}	-1.0414^{**}	-7.1547^{***}
		(0.4517)	(0.7307)	(0.3326)	(0.4977)	(0.4395)	(0.7371)
Firm characteristics	YES	NO	YES	NO	YES	NO	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES
Observation	506,514	368,333	368,333	506,514	506,514	368,333	368,333
Adjusted R^2	0.0897	0.3792	0.3844	0.3563	0.4161	0.1912	0.2164
F value	524.69						

Notes: In panels A and B, we employ the interaction term of distance from port and exchange rate as IV. In particular, in panel B, we remove any firms with changing located cities. The column (1) shows the first stage of 2SLS estimation, and the dependent variable is whether the firm exports to the USA. Columns (2)-(7) show the second stage, and dependent variables are emission intensity, output value, and emission levels. We employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

policy uncertainty aggravates or reduces emissions. In columns (6) and (7), we investigate the impact of decrease in trade policy uncertainty on firms' emission levels. The coefficients on $TPU_s \times Post_t \times \widehat{USEX_{ispt}}$ are not statistically significant. These results suggest that for firms which export to the USA, the impact of trade policy uncertainty on emission levels is not significant. These results confirm the Proposition 2. Namely, the impact of decrease in trade policy uncertainty on emission levels is uncertain, which depends on the changes in emission intensity and output value. The decrease in trade policy uncertainty not only reduces emission intensity but also expands output scale. These two effects offset each other. As a result, the net effect on emission levels is not significant. Combining all columns, the decrease in trade policy uncertainty does not significantly aggravate firms' emission levels, while firms expand output scale. Besides, these firms reduce emission intensity. Therefore, we conclude that the decrease in trade policy uncertainty helps exporting firms to improve environmental performance.

In addition, the distance from the port is not purely exogenous. The reason is that firms can change located cities and thereby change the distance from the port. Namely, firms which export to the USA may self-select to move to cities which are closer to the port. This may lead to the bias of IV estimation. Thus, we remove the firms which change their located cities. This ensures that our samples are located in the same cities and mitigates the interference of self-selection. The panel B of Table 4 reports these results. The column (1) shows the first stage of 2SLS estimation. We still find that the interaction term is negatively correlated with exporting to the USA. The columns (2)-(7) show the second stage. The results indicate that for firms which export to the USA, the decrease in trade policy uncertainty not only reduces emission intensity but also expands output scale. Trade policy uncertainty has no significant impact on emission levels. After removing firms with changing locations, our conclusion does not change. By a comparison, the specification of panel B can better address the endogeneity of export behavior. In subsequent analyses, we remove any firms with changing located cities.

5.2. Controlling for environmental regulation

5.2.1. Domestic environmental regulation

The above result shows that the decrease in trade policy uncertainty reduces firms' emission intensity. However, domestic environmental regulation affects both pollution and export behavior (Shi and Xu, 2018). During the period of this study, there are significant changes in environmental regulation in China. Thus, we need to prove that the reduction in firms' emission intensity is indeed due to decreasing trade policy uncertainty instead of domestic environmental regulation.

According to Shi and Xu (2018), environmental regulation is mainly reflected at province-time level in China. In Eq. (38), we employ province-year fixed effect to capture the potential effect of environmental regulation. However, our IV (distance from port) is a region-level variable related to the stringency of environmental regulation. Coastal cities usually have stricter environmental regulation. The IV may affect pollution emissions by the channel of domestic environmental regulation. To address this issue, we control for environmental regulation at other levels. Shi and Xu (2018) suggest that in China, different provinces have differentiated environmental regulations for different industries. Liu et al. (2021) suggest that China's environmental regulation is reflected at the city level, such as China's Key Cities for Air Pollution Control. Namely, we should control for the influencing factors at industry-province and city levels.

Columns (1)-(3) of Table 5 report these results. The column (1) controls for industry-province-year fixed effect. The column (2) further controls for city fixed effect. In the column (3), we are stricter in controlling industry-city fixed effect. After controlling for various levels of environmental regulations, we can better identify the environmental effect of trade policy uncertainty. From columns (1)-(3), all results indicate that for firms which export to the USA, the decrease in trade policy uncertainty reduces emission intensity. Even if we strictly control for domestic environmental regulation, our conclusion is still robust.

Table 5. Controlling for environmental regulation

	Domestic environmental regulation				
	Industry-province-year controls	Industry-province-year and city controls	Industry-province-year and industry-city controls	Foreign environmental regulation	Domestic and foreign environmental regulation
	(1)	(2)	(3)	(4)	(5)
$TPU_s \times Post_t \times \widehat{USEX_{ispt}}$	−4.5300**	−4.1279**	−3.8191**	−5.4875***	−3.6853*
	(1.9717)	(1.9543)	(1.9269)	(1.7394)	(1.9261)
Other variables	YES	YES	YES	YES	YES
Industry-time FE	NO	NO	NO	YES	NO
Province-time FE	NO	NO	NO	YES	NO
Industry-province-time FE	YES	YES	YES	NO	YES
City FE	NO	YES	NO	NO	NO
Industry-city FE	NO	NO	YES	NO	YES
Foreign environmental regulation	NO	NO	NO	YES	YES
Observation	367,430	367,426	366,739	368,333	366,739
Adjusted R^2	0.4206	0.4416	0.4741	0.3875	0.4762

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table only shows the result for the second stage of 2SLS estimation. Dependent variables are SO_2 emission intensity. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

5.2.2. Foreign environmental regulation

In addition to domestic environmental regulations, environmental regulations of importing countries are likely to affect exporting firms' pollution emissions (Antweiler et al. 2001). There are time-varying environmental regulations in the USA and other importing countries. Thus, we need to control for foreign environmental regulations.

According to Copeland and Taylor (1994), high-income countries usually have stricter environmental regulations, while low-income countries have looser regulations. We control for export destinations to capture the impacts of foreign environmental regulations. Specifically, we divide export destinations into high-income and low-income countries. Referring to Lin and He (2023b), we distinguish between two types of countries according to whether the country is an OECD country. Given that foreign environmental regulations change over time, we control for interaction terms between the dummies of export destinations ($HighIncome_{ispt}$ and $LowIncome_{ispt}$) and the dummies of different years. If a firm exports to OECD countries, $HighIncome_{ispt} = 1$; otherwise, $HighIncome_{ispt} = 0$. If a firm exports to non-OECD countries, $LowIncome_{ispt} = 1$; otherwise, $LowIncome_{ispt} = 0$. In addition, our study focuses on the event that the USA granted PNTR to China. We regard the USA as a special export destination. We further control for environmental regulations of the USA by the interaction term between $USEX_{ispt}$ and the dummies of different years.

The column (4) of Table 5 reports these results. We find that for firms exporting to the USA, the decrease in trade policy uncertainty leads to lower emission intensity. Furthermore, we simultaneously control for both domestic and foreign environmental regulations, which is reported in the column (5) of Table 5. The result still shows that the decrease in trade policy uncertainty helps to pollution reduction. After controlling for domestic and foreign environmental regulation, the results are supportive of our baseline conclusion.

Table 6. More discussion for export behavior

	The first stage	The second stage		
	Export behavior	Emission intensity	Output value	Emission levels
	(1)	(2)	(3)	(4)
Panel A: Export or not				
$\ln Distance_{ispt} \times Exchange_t$	-0.2095^{***}			
	(0.0098)			
$TPU_s \times Post_t \times \widehat{EX_{ispt}}$		-2.3090^{***}	2.3075^{***}	0.1050
		(0.6310)	(0.4141)	(0.5964)
Other variables	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES
Observation	524,270	385,554	524,270	385,554
Adjusted R^2	0.2470	0.3926	0.4372	0.2169
F value	1814.71			
Panel B: Export intensity				
$\ln Distance_{ispt} \times Exchange_t$	-0.1312^{***}			
	(0.0062)			
$TPU_s \times Post_t \times \widehat{EXI_{ispt}}$		-2.7906^{***}	3.2059^{***}	0.1858
		(0.9826)	(0.6616)	(0.9179)
Other variables	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES
Observation	524,270	385,554	524,270	385,554
Adjusted R^2	0.2765	0.3926	0.4373	0.2169
F value	1340.60			

Notes: Panels A and B focus on all exporters and firms' export intensity, respectively. We employ the interaction term of distance from port and exchange rate as IV and remove any firms with changing located cities. The column (1) shows the first stage of 2SLS estimation, and dependent variables are whether the firm exports to foreign countries (in panel A) and export intensity (in panel B). Columns (2)-(4) show the second stage, and dependent variables are emission intensity, output value, and emission levels. We employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: $^{***}1\%$, $^{**}5\%$, $^{*}10\%$.

5.3. More discussions for export behavior

5.3.1. Exporting to all countries

This study employs the PNTR granted to China by the USA in 2002 as an event shock. This event involves the trade policy of USA, so we mainly focus on firms which export to the USA. According to Feng et al. (2017), this event shock not only affects firms exporting to the USA but also affects firms exporting to other countries. As a result, we turn to examine the environmental effect of trade policy uncertainty on all exporting firms.

We employ a dummy of exporting to foreign countries (EX_{ispt}) to replace $USEX_{ispt}$. If a firm exports to foreign countries, $EX_{ispt} = 1$; otherwise, $EX_{ispt} = 0$. We show the result in the panel A of Table 6. We employ the interaction term of the distance from the port and exchange rate as IV of exporting. The column (1) shows that if firms are closer to the port and US dollar exchanges more Chinese yuan, they are more inclined to export products. Other columns show that the decrease in trade policy uncertainty reduces emission intensity and expands output scale of exporting firms. The impact on emission levels is statistically insignificant. Compared with the panel B of Table 1, trade policy uncertainty has a minor effect on emission intensity of all exporters relative to firms exporting to the USA.

5.3.2. Export intensity

There is a phenomenon that different exporters have different export intensities. Some exporters focus on domestic market, and other exporters depend on foreign markets. According to Richter and Schiersch (2017) and Lin and He (2023a), firms with different export intensities have differentiated emissions. Since trade policy uncertainty mainly affects exporters, we infer that trade policy uncertainty may have a greater impact on firms with higher export intensity.

We employ export intensity (EXI_{ispt}) to replace $USEX_{ispt}$. EXI_{ispt} is calculated by the ratio of export to sale value. The panel B of Table 6 reports these results. We employ the interaction term of the distance from the port and exchange rate as IV of export intensity. The column (1) shows that if located cities are closer to the port and US dollar exchanges more Chinese yuan, firms have higher export intensity. Columns (2)-(4) show that for firms with higher export intensity, the decrease in trade policy uncertainty reduces emission intensity and expands output. The net effect on emission levels is insignificant. These results confirm our inference that trade policy uncertainty has greater environmental effect on firms with higher export intensity.

5.4. The tests for DDD model

5.4.1. Anticipation effect and dynamic effect

A prerequisite for DDD model is that samples from different groups must have the common pre-trend in dependent variables. In this study, the common pre-trend means that firms from different groups had no ex-ante difference in environmental performance before the USA granted PNTR to China in 2002. Above results indicate that the decrease in trade policy uncertainty significantly reduces emission intensity and expands output scale. Thus, we need to examine the anticipation effects of trade policy uncertainty on emission intensity and output scale. We replace $Post_t$ of Eq. (38) by the dummies of different years. In this estimation, we focus on firms which export to the USA and all countries. This method also examines the dynamic effect of trade policy uncertainty. Figure 2 shows these results. In panels (a) and (b), we focus on firms which export to the USA and regard 2000 as the baseline period. In panels (b) and (d), we focus on all exporters and regard 1998-1999 as baseline periods.

First, we employ emission intensity as dependent variables. Panels (a) and (c) show that before 2002, the coefficients are statistically insignificant. After 2002, the coefficients are all negative and essentially significant. These results suggest that compared with the baseline periods, firms' emission intensity has no significant change before 2002. This proves that before the USA granted PNTR to China, firms from different groups had a common pre-trend in emission intensity. Namely, the decrease in trade policy uncertainty reduces emission intensity, rather than the ex-ante difference in emission intensity between firms from different groups. In addition, dynamic effects suggest that in the first year of event shock, firms' emission intensity immediately decreases. In following years (2003-2012), the decrease in trade policy uncertainty always reduces emission intensity, and this effect has an increasing trend.

Second, we employ output value as dependent variables. Panels (b) and (d) show that before 2002, the coefficients are not significant. After 2002, the coefficients are significantly positive. These results suggest that before the USA granted PNTR to China, firms' output value had a common pre-trend. Namely, the decrease in trade policy uncertainty expands output scale rather than the ex-ante difference in output value. In addition, dynamic effects indicate that after 2002, firms immediately expand output scale. From 2002 to 2012, these effects firstly increase and then decrease. After 2008, these effects begin to decrease continuously. The possible reason is that firms' exports are influenced by the global economic crisis in 2008, and these firms thereby reduce production scale.

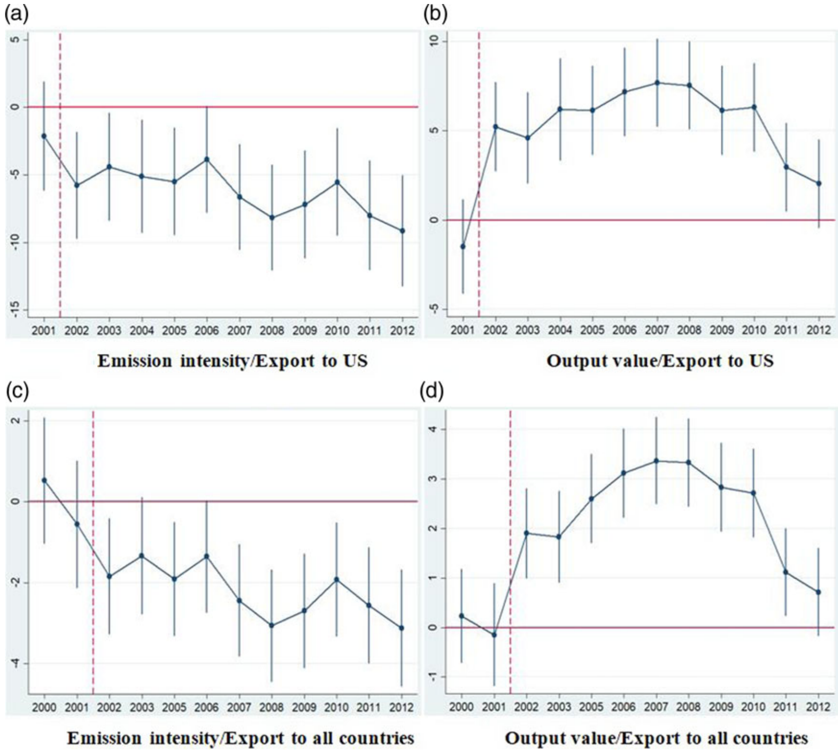

Figure 2. Anticipation effect and dynamic effect. Note: We employ the interaction term of distance from port and exchange rate as IV of export behaviors and remove any firms with changing located cities. Panels (a) and (b) focus on firms exporting to the USA and regard 2000 as the baseline period. Panels (c) and (d) focus on all exporters and regard 1998 and 1999 as baseline periods. In panels (a) and (c), dependent variables are emission intensity, and in panels (b) and (d), dependent variables are output value. We employ SO_2 as the pollutant. The level of confidence interval is 90%.

5.4.2. Placebo

To ensure that the change of firms' environmental performance is caused by the decrease in trade policy uncertainty of the USA granting PNTR to China in 2002, we design a placebo test. Specifically, we employ the samples before this event to construct false event shocks. We assume that the USA granted PNTR to China in 2001 or 2000. We employ these false events and the samples before 2002 to estimate the results. Table 7 reports the results of placebo tests, which focus on exporting to the USA and all countries. In columns (1)-(6), we assume the event of the USA granting PNTR to China occurred in 2001, and in columns (7)-(9), we assume this event occurred in 2000. From all columns, estimated coefficients are not significant. These results suggest that false events cannot change firms' environmental performance. Namely, before the event of the USA granting PNTR to China, trade policy uncertainty does not affect environmental performance. Our baseline results are definitely driven by the decrease in trade policy uncertainty in 2002.

5.5. Other robustness checks

To ensure the robustness of this conclusion, we do following robustness checks. Table 8 reports the results of robustness checks. First, in baseline estimation, we employ SO_2 as the pollutant. The literature considers that for different pollutants, the impacts of trade policy on firm-level pollution emissions are different (Cherniwchan, 2017). To ensure that the impact of trade policy uncertainty on pollution emissions does not vary with pollutants, we employ other pollutant for robustness check. Since SO_2 is an air pollutant, we employ COD which is the pollutant in wastewater. COD

Table 7. Placebo: changing the time of the event

	Assuming the event occurred in 2001						Assuming the event occurred in 2000		
	Emission intensity (1)	Output value (2)	Emission levels (3)	Emission intensity (4)	Output value (5)	Emission levels (6)	Emission intensity (7)	Output value (8)	Emission levels (9)
$TPU_s \times Post_t^{2001} \times \widehat{USEX_{ispt}}$	−2.1359	−1.5922	−1.1484						
	(2.4371)	(1.6001)	(2.1570)						
$TPU_s \times Post_t^{2001} \times \widehat{EX_{ispt}}$				−0.8776	−0.1910	0.2715			
				(0.8546)	(0.5717)	(0.7723)			
$TPU_s \times Post_t^{2000} \times \widehat{EX_{ispt}}$							−0.1542	0.1540	1.1856
							(0.8056)	(0.5126)	(0.7295)
Other variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observation	44,650	55,510	44,650	87,229	106,043	87,229	87,229	106,043	87,229
Adjusted R^2	0.2840	0.2259	0.2036	0.2949	0.2317	0.2117	0.2948	0.2317	0.2117

Notes: In this table, we employ the samples before 2002 for analysis. We employ the interaction term of distance from port and exchange rate as IV of export behaviors and remove any firms with changing located cities. This table only shows the results for the second stage of 2SLS estimation. In columns (1)-(6), we assume the event that the USA granted PNTR to China occurred in 2001 and focus on exporting to the USA and all countries. In columns (7)-(9), we assume this event occurred in 2002 and focus on all exporters. We employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

Table 8. Other robustness checks

	Other pollutants	Other calculation for emission intensity		Other measurement for TPU	Other periods	Firms that are present before and after 2002
	COD (1)	Emissions/ Sales (2)	Emissions/ Employees (3)	Handley and Limão (2017) (4)	1998-2007 (5)	(6)
$TPU_s \times Post_t \times \widehat{USEX_{ispt}}$	−8.3656***	−5.7428***	−4.5330***	−2.2909***	−2.9564*	−3.5157*
	(1.8290)	(1.7531)	(1.5574)	(0.7844)	(1.7182)	(1.8601)
Other variables	YES	YES	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES
Observation	380,814	342,975	368,333	368,333	198,870	181,262
Adjusted R^2	0.3494	0.3860	0.2961	0.3843	0.2916	0.4051

Notes: Dependent variables are emission intensity. Except for the column (1), we employ SO_2 as the pollutant. We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table only shows the second stage of 2SLS estimation. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

is one of the key pollutants monitored in China. CESFD provides information on firm-level COD emissions. This result is reported in the column (1). We find that employing COD as the pollutant, the decrease in trade policy uncertainty leads to lower emission intensity. When we employ other pollutant for analysis, our conclusion is still robust.

Second, this study employs the ratio of emission levels to output value to calculate firms' emission intensity. The literature also employs emissions-to-sales and emissions-to-employees ratios to reflect emission intensity (Cherniwchan, 2017). According to Brucal et al. (2019) and Lin and

He (2023a), employing output value to calculate emission intensity may lead to markup-driven bias. This is because output value is significantly influenced by markups. In China, manufacturing markups increase rapidly and differentially across firms (Lu and Yu, 2015; Brandt et al. 2017). The number of employees can reflect the scale of firms and is not influenced by markups. Employing emissions-to-employees ratio can effectively address markup-driven bias. Thus, we employ emissions-to-sales and emissions-to-employees ratios to calculate emission intensity for robustness checks. The columns (2) and (3) report these results, which still show that the decrease in trade policy uncertainty reduces emission intensity. Our conclusion holds very well in the situation of employing other methods to calculate emission intensity.

Third, this study measures trade policy uncertainty according to Pierce and Schott (2016). Handley and Limão (2017) provide another method for measurement. To ensure that our conclusion does not vary with the measurement of trade policy uncertainty, we measure this indicator by the method of Handley and Limão (2017). This measurement is carried out in two steps. The first one is to calculate product-level trade policy uncertainty by $TPU_k = 1 - \left(\frac{Tariff_k^{Col2}}{Tariff_k^{MFN}}\right)^{-\sigma}$. Similar to Handley and Limão (2017), we set $\sigma = 3$. The second is to aggregate trade policy uncertainty at the industry level. The column (4) reports this result. The result supports that the decrease in trade policy uncertainty reduces emission intensity. Even if we employ other method to measure trade policy uncertainty, our conclusion holds very well.

Fourth, in this study, we employ the data of Chinese firms from 1998 to 2012. To ensure that the impact of trade policy uncertainty on environmental performance does not change in different periods, we employ the samples from different periods for robustness check. From 1998 to 2012, there is an event which brings an uncertainty to international trade and profoundly affects firms' export behavior. Namely, the global economic crisis occurred in 2008. We remove any samples after 2008. The column (5) reports this result. The result indicates that for 1998-2007, the decrease in trade policy uncertainty reduces emission intensity. When we employ the samples from different periods for analysis, the result is supportive of our conclusion.

Fifth, in China, many firms entered and exited the industry during the period of our study. The PNTR granted to China by the USA occurred in 2002. Some firms did not enter before 2002, and some firms exited after 2002. According to Cherniwchan (2017), firms' entry and exit may affect the environmental effects of trade policy. Namely, new entrants may be cleaner, and firms exiting the industry may be dirtier. Thus, we employ the samples that are present before and after 2002 for robustness check, which is reported in the column (5). The result indicates that the decrease in trade policy uncertainty leads to lower emission intensity. Even if we exclude the interference of firms' entry and exit, our conclusion is still robust.

5.6. Mechanism

Above results show that the decrease in trade policy uncertainty leads to lower emission intensity. The Proposition 3 suggests that improving energy efficiency is an important mechanism. Thus, we employ energy efficiency as a major mechanism to examine how the decrease in trade policy uncertainty reduces emission intensity. We also examine other potential mechanisms of abatement technology and energy structure.

5.6.1. Energy efficiency

Firms' pollution emissions mainly come from energy consumption. The reduction in emission intensity may be due to improving energy efficiency (Gutiérrez and Teshima, 2018; Brucal et al. 2019; Lin and He, 2023a). In theoretical section, we prove that the decrease in trade policy uncertainty is conducive to reducing expected trade cost and enabling firms to invest more in production technology. Then, firms upgrade production technology and thereby improve energy efficiency. The Proposition 3 indicates that energy efficiency is an important mechanism between

Table 9. Mechanism: energy efficiency

	Energy efficiency (1)	Energy consumption (2)	Energy efficiency (coal) (3)	Coal consumption (4)	Labor productivity (5)	TFP (OLS) (6)	TFP including energy (OLS) (7)
$TPU_s \times Post_t \times \widehat{USEX}_{ispt}$	6.3714***	−1.7731	6.2437***	−0.8354	1.9343**	2.4032***	1.9567**
	(1.4794)	(1.3666)	(1.7231)	(1.5515)	(0.7961)	(0.7995)	(0.8837)
Other variables	YES	YES	YES	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES
Observation	331,518	331,518	289,333	289,333	506,514	506,514	331,518
Adjusted R^2	0.4237	0.2955	0.4164	0.3021	0.5036	0.3797	0.3943

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table shows the second stage of 2SLS estimation. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

trade policy uncertainty and emission intensity. We examine the impact of decrease in trade policy uncertainty on energy efficiency, which is reported in Table 9.

CESFD provides information on coal, fuel oil, and clean gas consumption. We aggregate firms' total energy consumption of three energies by standard coal coefficient.[13] Then, we measure energy efficiency by the ratio of output value to total energy consumption. We examine the impact of trade policy uncertainty on energy efficiency, which is reported in column (1). The coefficient on $TPU_s \times Post_t \times \widehat{USEX}_{ispt}$ is significantly positive. This result indicates that for firms exporting to the USA, the decrease in trade policy uncertainty leads to higher energy efficiency. This confirms the Proposition 3. Namely, improving energy efficiency is an important mechanism by which the decrease in trade policy uncertainty reduces emission intensity. The explanation is that decreasing uncertainty reduces expected trade cost of exporting firms. Thus, these firms can invest more to upgrade production technology and thereby improve energy efficiency.

Energy efficiency is measured by the ratio of output value to energy consumption. The improvement in energy efficiency may be due to upgrade production technology or reduce energy consumption. The latter means that firms may use other production factors to replace energy. To eliminate this interference, we examine the impact of trade policy uncertainty on energy consumption. The column (2) reports this result. We find that the estimated coefficient is insignificant. This suggests that trade policy uncertainty has no significant impact on energy consumption. In addition, our baseline results show that the decrease in trade policy uncertainty significantly expands output scale. These firms expand output scale without significant change in energy consumption. We conclude that the decrease in trade policy uncertainty improves energy efficiency through upgrading technology rather than reducing energy consumption.

Pollution emissions mainly come from the consumption of pollution-intensive coal. Relatively, fuel oil and clean gas are cleaner. As a result, coal efficiency may play a more important role in the relationship between trade policy uncertainty and emission intensity. We re-measure energy efficiency by the ratio of output value to coal consumption. We examine the impact of trade policy uncertainty on both coal efficiency and coal consumption. The columns (3) and (4) report these results. The results show that the decrease in trade policy uncertainty improves coal efficiency, but has no significant impact on coal consumption. These results are consistent with the results based on total energy consumption and also support the Proposition 3.

Moreover, our theoretical section suggests that after decreasing trade policy uncertainty, exporting firms improve energy efficiency through upgrading production technology and improving productivity. Actually, energy efficiency is a special kind of production technology and productivity. Thus, we examine the impact of decrease in trade policy uncertainty on productivity.

Table 10. Mechanism: abatement technology

	Number of abatement equipment (1)	Number of desulfurization equipment (2)	Capacity of abatement equipment (3)	Capacity of desulfurization equipment (4)	Removal rate of emissions (5)	Emissions/ Energy (6)	Emissions/ Coal (7)
$TPU_s \times Post_t \times \widehat{USEX}_{ispt}$	0.0147	0.2926	−4.5389	0.6861	0.0630	1.2571	1.2618
	(0.4761)	(0.2798)	(3.8692)	(0.9961)	(0.1643)	(0.9256)	(0.9385)
Other variables	YES	YES	YES	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES
Observation	451,841	422,858	422,858	422,858	368,511	320,057	287,830
Adjusted R^2	0.1509	0.0995	0.1315	0.0806	0.0934	0.1475	0.1560

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table shows the second stage of 2SLS estimation. In columns (5)-(7), we employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

We employ three indicators to represent productivity. The first one is labor productivity which is calculated by output-to-employees ratio. The second is total factor productivity (TFP). We employ labor and capital as production factors and output value as outcome variable. We use ordinary least square (OLS) method and control for industry-year and province-year fixed effects to estimate TFP. For the third indicator, since our production function in theoretical model includes energy, we put energy as a kind of production factor into TFP estimation. Namely, we employ labor, capital, and energy as production factors for TFP estimation. Columns (5)-(7) report these results. We find that estimated coefficients are statistically positive. These results indicate that the decrease in trade policy uncertainty can upgrade production technology and improve productivity (including labor productivity and TFP). These effects further drive the improvement in energy efficiency, and reduce emission intensity.

5.6.2. Abatement technology

Terminal abatement helps to reduce firms' pollution emissions. The reduction in emission intensity may be due to applying more abatement equipments and improving abatement technology (Forslid et al. 2018; Liu et al. 2021). Given that abatement investment requires higher fixed costs, firms with higher productivity and larger scale are more likely to invest in abatement equipment (Forslid et al. 2018). Above analyses have confirmed that the decrease in trade policy uncertainty improves production technology and expands output scale. These effects may indirectly enable firms to invest in abatement equipment and improve abatement technology. Thus, abatement technology is a potential mechanism by which trade policy uncertainty affects emission intensity. We examine the impact of decrease in trade policy uncertainty on abatement technology, which is reported in Table 10.

CESFD provides abundant information on abatement equipment at the firm level, including the numbers of abatement equipment for waste gas and desulfurization equipment. Abatement equipment can reflect technical level related to terminal pollution reduction. We examine the impact of trade policy uncertainty on the number of abatement equipment. Columns (1) and (2) report these results. The coefficients on $TPU_s \times Post_t \times \widehat{USEX}_{ispt}$ are statistically insignificant. These results show that trade policy uncertainty cannot significantly change the numbers of abatement equipment. These suggest that abatement investment is not a mechanism by which the decrease in trade policy uncertainty reduces emission intensity.

CESFD also provides the information on the capacity of abatement equipment (including abatement equipment for waste gas and desulfurization equipment). This capacity refers to the amount of pollution handled by abatement equipment per hour, which can reflect firm-level abatement technology. We examine the impact of decrease in trade policy uncertainty on the capacity of abatement equipment. Columns (3) and (4) report these results. We find that estimated coefficients are not significant. These results suggest that trade policy uncertainty has no significant impact on the capacities of abatement equipment and desulfurization equipment, which is similar to the results of the number of abatement equipment.

Abatement technology involves firms' capacity to remove pollution (Gutiérrez and Teshima, 2018; Liu et al. 2021). Firms can install more abatement equipments to gain higher removal rate of emissions. In other words, we can employ the removal rate of emissions to reflect abatement technology. CESFD provides the data on the removal levels of pollution. We calculate the levels of pollution generation by the sum of emission levels and removal levels. Then, we calculate the removal rate of emissions by the ratio of removal levels to generation levels. We examine the impact of trade policy uncertainty on the removal rate of emissions. The column (5) shows that the estimated coefficient is not significant. This result implies that trade policy uncertainty does not lead to significant change in the removal rate of emissions.

In the Section 2, we use the emission levels per unit of energy consumption to reflect abatement technology when we decompose emission intensity. This is because firms' pollution emissions mainly come from energy consumption. Firms with advanced abatement technology have stronger capacity to remove emissions and thereby reduce emission levels per unit of energy consumption (Gutiérrez and Teshima, 2018; Lin and He, 2023a). We examine the impact of trade policy uncertainty on emissions-to-energy ratio. In addition, given that pollution emissions are mainly from pollution-intensive coal consumption, we employ the ratio of emission levels to coal consumption for analysis. Columns (6)-(7) report these results. We find that estimated coefficients are insignificant. These results indicate that the decrease in trade policy uncertainty cannot affect the emission levels per unit of energy consumption (or coal consumption).

Altogether, Table 10 indicates that trade policy uncertainty has no significant impact on firms' abatement equipment and abatement technology. Thus, abatement technology is not the mechanism by which the decrease in trade policy uncertainty reduces emission intensity. This conclusion is similar to Gutiérrez and Teshima (2018). Namely, firms in developing countries reduce emissions by improving energy efficiency rather than improving abatement technology. In addition, this conclusion is different from the literature that shows abatement technology is the mechanism by which trade affects firms' pollution emissions (Forslid et al. 2018; Rodrigue et al. 2022a; Kwon et al. 2023). However, these works focus on firms' export and import behaviors as well as trade liberalization, and we analyze the mechanism for trade policy uncertainty.

5.6.3. Energy structure

Optimizing energy structure contributes to pollution reduction. The reduction in emission intensity may be due to that firms reduce pollution-intensive coal consumption, and they input more clean-intensive energies (fuel oil and clean gas). Considering that the cost of clean energy is relatively higher, firms with lower productivity and smaller scale prefer to consume coal with lower cost. Above results show that the decrease in trade policy uncertainty improves production technology and expands output scale, which may indirectly promote firms to input more clean energies and optimize energy structure. That is to say, energy structure is a potential mechanism by which trade policy uncertainty affects emission intensity.

Energy structure represents the proportions of pollution-intensive and clean-intensive energies. We separately employ the ratios of coal, fuel oil and clean gas consumptions to total energy consumption to calculate energy structure. Firms consuming more coals have higher emission intensity, while firms relying on fuel oil and clean gas are cleaner. We examine the impact of decrease in trade policy uncertainty on energy structure. Table 11 reports these results. From the column (1), the coefficient on $TPU_s \times Post_t \times \widehat{USEX_{ispt}}$ is significantly positive. This result suggests that the decrease in trade policy uncertainty leads to higher coal-to-energy ratio. From the

Table 11. Mechanism: energy structure

	Coal/ Energy (1)	Fuel oil/ Energy (2)	Clean gas/ Energy (3)
$TPU_s \times Post_t \times \widehat{USEX_{ispt}}$	0.6145**	−0.2662	−0.3484***
	(0.3078)	(0.3006)	(0.1116)
Other variables	YES	YES	YES
Industry-time FE	YES	YES	YES
Province-time FE	YES	YES	YES
Observation	331,518	331,518	331,518
Adjusted R^2	0.2851	0.2668	0.1721

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table shows the second stage of 2SLS estimation. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

column (2), the estimated coefficient is not significant. This indicates that trade policy uncertainty has no significant impact on the ratio of fuel oil to total energy. The column (3) shows that the estimated coefficient is significantly negative. This implies that the decrease in trade policy uncertainty makes firms input less clean gas and reduce gas-to-energy ratio.

Altogether, Table 11 suggests that the decrease in trade policy uncertainty increases the proportion of pollution-intensive coal consumption, and reduces the proportion of clean-intensive energy consumption. Namely, the decrease in trade policy uncertainty cannot optimize energy structure to the cleaner production. Firms' energy structure becomes dirtier. The possible reason is that after the USA granted PNTR to China in 2002, Chinese firms make use of low-cost advantage to enter the export market and expand export scale (Pierce and Schott, 2016; Handley and Limão, 2017; Feng et al. 2017). To further reduce costs, these firms may input lower-cost but dirtier coal. Therefore, energy structure is not the mechanism by which the decrease in trade policy uncertainty reduces emission intensity.

5.7. Heterogeneous tests

5.7.1. Different industries

We employ pollution intensity and factor intensity to distinguish different industries. Based on these classifications, we examine the heterogeneous impacts of trade policy uncertainty on pollution emissions in terms of different industry types. Table 12 reports these results.

First, Shapiro (2021) indicates that trade policy has an environmental bias. Tariffs for pollution-intensive industries are fewer relative to clean-intensive industries. Industrial emissions mainly come from pollution-intensive industries. These industries are major industries of environmental supervision and control, and they have greater potential for pollution reduction. Thus, we infer that for pollution-intensive industries, trade policy uncertainty has a greater impact on pollution emissions. We calculate average emission intensity from 1998 to 2012 at the industry level[14] to distinguish between pollution-intensive and clean-intensive industries and examine the heterogeneous impacts of trade policy uncertainty.

From columns (1) and (3), the coefficients on $TPU_s \times Post_t \times \widehat{USEX_{ispt}}$ are significantly negative. For pollution-intensive and clean-intensive industries, the decrease in trade policy uncertainty reduces emission intensity. The absolute value of the coefficient in column (1) is relatively greater. These confirm our inference. The decrease in trade policy uncertainty leads to a greater pollution reduction for pollution-intensive industries. The possible reason is that these industries have more emissions and are strictly regulated, which has greater potential for pollution reduction. From columns (2) and (4), estimated coefficients are not significant.

Table 12. Heterogeneous tests: different industries

	Pollution-intensive		Clean-intensive		Capital-intensive		Labor-intensive	
	Emission intensity (1)	Emission levels (2)	Emission intensity (3)	Emission levels (4)	Emission intensity (5)	Emission levels (6)	Emission intensity (7)	Emission levels (8)
$TPU_s \times Post_t \times \widehat{USEX_{ispt}}$	−12.7366***	−4.0854	−3.8908*	1.7296	−7.1801*	−2.5436	−3.4705*	1.2515
	(4.0167)	(3.9266)	(2.0061)	(1.8250)	(3.7819)	(3.8450)	(1.9324)	(1.7303)
Other variables	YES	YES	YES	YES	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES	YES	YES	YES	YES
Observation	208,900	208,900	159,433	159,433	215,855	215,855	152,478	152,478
Adjusted R^2	0.3710	0.1502	0.3159	0.1661	0.3922	0.1679	0.3100	0.1661

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table shows the second stage of 2SLS estimation. Dependent variables include emission intensity and emission levels. We employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

Second, for a long time, China has an advantage of exports in labor-intensive industries (He et al. 2020c). These industries represent backward technology, and they are difficult to gain technical upgrading. On the contrary, capital-intensive industries have advanced technology and play an important role in technical upgrading. Capital-intensive industries are more likely to benefit from decreasing trade policy uncertainty. In addition, capital-intensive industries are usually pollution-intensive industries with greater potential to reduce emissions. Thus, we infer that for capital-intensive industries, trade policy uncertainty has greater impact on pollution emissions. We refer to Lin and He (2023a) and calculate industry-level capital intensity.[15] Then, we distinguish between capital-intensive and labor-intensive industries to examine the heterogeneous impacts of trade policy uncertainty.

From columns (5) and (7), estimated coefficients are significantly negative. For capital-intensive and labor-intensive industries, the decrease in trade policy uncertainty leads to lower emission intensity. The absolute value of the coefficient in the column (5) is relatively greater. These results confirm our inference. The decrease in trade policy uncertainty causes a greater effect on pollution reduction of capital-intensive industries. The possible reasons are that on the one hand, capital-intensive industries represent advanced technology, which are more likely to gain technical upgrading. On the other hand, capital-intensive industries are pollution-intensive and have greater potential for pollution reduction. From columns (6) and (8), estimated coefficients are statistically insignificant.

5.7.2. Different regions

We employ geographical location to distinguish different regions. Geographic location is closely related to firms' export behavior as well as trade policy uncertainty. Compared with inland provinces in China, coastal provinces are developed and have lower trade costs. Coastal firms are more likely to export products and be influenced by trade policy uncertainty. Thus, we infer that for coastal provinces, trade policy uncertainty has a greater impact on pollution emissions.

We distinguish between coastal and inland provinces to examine the heterogeneous impacts of trade policy uncertainty on pollution emissions. Table 13 reports these results. From the column (1), the coefficient on $TPU_s \times Post_t \times \widehat{USEX_{ispt}}$ is significantly negative. However, the coefficient is statistically insignificant in column (3). These results suggest that the decrease in trade policy uncertainty can only reduce emission intensity in coastal provinces, but has no significant impact on emission intensity in inland provinces. These results confirm our inference. Namely, pollution reduction caused by decreasing trade policy uncertainty mainly occurs in coastal provinces. The possible reason is that coastal provinces have lower trade costs, and firms located in these

Table 13. Heterogeneous tests: different regions

	Coastal provinces		Inland provinces	
	Emission intensity (1)	Emission levels (2)	Emission intensity (3)	Emission levels (4)
$TPU_s \times Post_t \times \widehat{USEX}_{ispt}$	-4.2045^{**}	-1.1466	-5.1096	2.7510
	(1.9994)	(1.8584)	(4.6312)	(4.3929)
Other variables	YES	YES	YES	YES
Industry-time FE	YES	YES	YES	YES
Province-time FE	YES	YES	YES	YES
Observation	216,683	216,683	151,650	151,650
Adjusted R^2	0.3392	0.2388	0.4268	0.1979

Notes: We employ the interaction term of distance from port and exchange rate as IV of exporting to the USA and remove any firms with changing located cities. This table shows the result for the second stage of 2SLS estimation. Dependent variables include emission intensity and emission levels. We employ SO_2 as the pollutant. The figures in parentheses are robust standard errors clustered at firm level. Significance: ***1%, **5%, *10%.

provinces are easily influenced by trade policy uncertainty. From columns (2) and (4), estimated coefficients are not significant.

6. Conclusion

In this study, we theoretically and empirically investigate the impact of trade policy uncertainty on firm-level pollution emissions. Based on Melitz's (2003) framework, we incorporate energy, pollution, and trade policy uncertainty to construct a theoretical model with heterogeneous firms. Regarding energy efficiency as a channel, we reveal the potential effect of trade policy uncertainty on emission intensity and emission levels. Then, we employ the data of Chinese manufacturing firms for empirical analysis. Specifically, we employ the event that the USA granted PNTR to China in 2002 as a quasi natural experiment and construct a DDD model to identify the causal effect of decrease in trade policy uncertainty on firms' pollution emissions.

Our results indicate that the decrease in trade policy uncertainty can reduce emission intensity and expand output scale of exporting firms, but the net effect on emission levels is not significant. Given that these firms do not significantly aggravate emission levels under the condition of output expansion, we conclude that the decrease in trade policy uncertainty improves environmental performance. Energy efficiency is the important mechanism between trade policy uncertainty and emission intensity. The decrease in trade policy uncertainty reduces firms' emission intensity mainly by upgrading production technology and thereby improving energy efficiency rather than improving abatement technology and optimizing energy structure. In addition, the pollution reduction caused by decreasing trade policy uncertainty mainly occurs in pollution-intensive and capital-intensive industries as well as coastal regions.

Altogether, we enrich the literature on trade-environment relationship and trade policy uncertainty by theoretically and empirically studying the impact of trade policy uncertainty on firm-level pollution emissions. In the context of de-globalization and Sino-US trade friction, our conclusions provide important implications. First, although the Sino-US trade war has been suspended, trade policy uncertainty still exists. Given that the decrease in trade policy uncertainty can improve firms' environmental performance, it is necessary to strengthen economic and trade ties among countries in the world. Namely, to achieve environmental protection and sustainable development, countries should promote free trade, reduce trade protection and thereby decrease the uncertainty of trade policy. Second, in view of that pollution reduction caused by decreasing trade policy uncertainty mainly occurs in exporting firms, it is important to promote the exports of firms. In particular, we should focus on firms' exports in pollution-intensive and capital-intensive industries as well as coastal regions. Third, the decrease in trade policy uncertainty reduces pollution emissions mainly by improving energy efficiency rather than improving abatement technology and optimizing energy structure. In this process, it is critical to guide firms to improve energy efficiency. However, firms cannot neglect to improve abatement technology and optimize energy structure, which are also important ways to achieve pollution reduction.

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Notes

1 Different from these works, we reveal the impact of trade policy uncertainty on firms' pollution emissions. Trade policy uncertainty and trade liberalization are two different concepts. Trade liberalization is a certain phenomenon that trade policies (such as tariffs) gradually decrease. Trade policy uncertainty refers to that external trade policies (such as tariffs) are uncertain in the future. It further leads to the uncertainty of trade costs, revenue, and profit of exporting firms, which brings a series of adverse effects (Pierce and Schott, 2016).

2 Shapiro and Walker (2018), Forslid et al. (2018) and Rodrigue et al. (2022a) also extend Melitz's (2003) model to analyze the relationship between trade and environment, which provide important theoretical foundations for subsequent analyses. Our theoretical framework is different from these works. First, the literature mainly focuses on the environmental effects of exporting and trade liberalization. Our study introduces trade policy uncertainty referring to Handley and Limão (2017) to analyze the environmental effect of this uncertainty. Trade policy uncertainty is different from trade liberalization in theoretical models, although both of them affect trade costs. Trade liberalization is a certain event that directly affects trade costs. Trade policy uncertainty affects expected trade costs, which indirectly affects production, profit, and behaviors of firms. Second, the literature mainly employs productivity and abatement investment as the mechanisms by which trade affects firms' pollution emissions. This study is the first to incorporate both energy consumption and energy efficiency. In particular, energy consumption produces pollution emissions. Thus, we can theoretically analyze a novel mechanism that trade policy uncertainty affects firms' pollution emissions through energy efficiency.

3 Imbruno and Ketterer (2018) and He and Huang (2022) also theoretically analyze the role of production technology between trade and firms' environmental performance. Imbruno and Ketterer (2018) analyze the role of energy efficiency. He and Huang (2022) use Melitz's (2003) model as the basic framework. Our theoretical analysis is different from these works. First, these two works focus on the impact of importing intermediate products. Our study analyzes the impact of trade policy uncertainty. Second, our study provides a more detailed process for the mechanism that trade policy uncertainty affects expected trade costs and investment in production technology. Then, it upgrades production technology and thereby improves energy efficiency.

4 Without this assumption, firms would continue to invest in production technology to gain more profits. As a result, firms do not have the optimal investment for production technology.

5 According to Melitz (2003) and Bustos (2011), tariff only affects variable costs rather than all costs. This is because tariffs need to be paid only after starting to export and vary with changes in export value.

6 If $\triangle t$ is smaller, firms' behaviors are unlikely to be affected by trade policy uncertainty regardless of higher or lower tariffs imposed by foreign country. It is because this higher tariff is not much higher than lower tariff, and they only have slightly different impacts on firms' behaviors. If $\triangle t$ is larger, this uncertainty would force firms to adjust their behaviors. This is because firms have a probability to face a much higher tariff. Firms would worry about higher trade cost in the future, which may bring a series of adverse effects (Pierce and Schott, 2016).

7 It does not mean that firms which sell in domestic market are entirely unaffected by trade policy uncertainty. Actually, trade policy uncertainty also affects domestic sales firms, but the impact of this uncertainty on exporting firms is much greater (Feng et al. 2017; Liu and Ma, 2020). To simplify theoretical analysis, we focus on exporting firms.

8 In this study, we focus on the environmental effect of decreasing trade policy uncertainty caused by the USA granted PNTR to China. In the context of de-globalization and Sino-US trade friction, trade policy uncertainty significantly increases (He et al. 2020c; Benguria et al. 2022). However, there are some similarities between these two events. First, both of them involve trade relationship between China and the USA which are the two largest economies in the world. Second, they are reflected in tariff uncertainty. Therefore, analyzing the impact of such uncertainty can provide implications for current de-globalization and Sino-US trade friction.

9 Capital intensity (KL_{ispt}) is calculated by the ratio of the value of fixed asset to the number of employees. Financing constraint ($Constraint_{ispt}$) is calculated by the ratio of interest expenditure to the value of fixed asset. If a firm is state-owned firm, $SOE_{ispt} = 1$; otherwise, $SOE_{ispt} = 0$. If a firm is foreign-funded firm, $Foreign_{ispt} = 1$; otherwise, $Foreign_{ispt} = 0$.

10 We do not control for firm fixed effect. The reason is that we employ the PNTR granted to China by the USA as an event shock, and employ DDD model to identify the impact of trade policy uncertainty. This shock occurred in 2002. In China, many firms did not enter the industry before 2002, and many firms exited after 2002. If we control for firm fixed effect, it is equivalent to estimating the result within the same firms. There is a problem that some firms enter (or exit) after 2002. These firms only have information after (or before) the shock, but have no information before (or after) the shock. In this case, the DDD estimation would be biased.

11 Data sources: Our calculation is according to the data of Gaud map.

12 Data sources: The China Statistical Yearbook.

13 Data source: The China Energy Statistical Yearbook.

14 Data source: Our calculations by the data from the China Statistical Yearbook.

15 Data source: Our calculations by the data from the China Statistical Yearbook.

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