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The equilibrium effects of environmental regulation on heterogeneous competing firms: Theory and evidence from Chinese manufacturing

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ABSTRACT

Environmental regulation has the potential to reshape market competition, thereby influencing the market power of regulated firms and potentially impacting social welfare. We show that in certain scenarios, both high-pollution and low-pollution firms may respond to environmental regulation by reducing overall output, thereby increasing price-marginal cost markups. This approach allows them to transfer some of the regulatory costs onto consumers. However, well-designed and appropriately implemented environmental regulations can still increase social welfare. Our empirical analysis of Chinese manufacturing firms supports this assertion, indicating that environmental regulations in China lead to an increase in markups while simultaneously reducing the welfare losses caused by markups.

1. Introduction

Following the 18th National Congress, China made a strategic decision to strengthen environmental protections. Consequently, the Chinese Central Government introduced a series of rules and regulations to reduce business' pollution emissions. These include the Action Plan for Air Pollution Prevention and Control (2013), the Implementation Regulations of the Environmental Protection Tax Law of the People's Republic of China (2017), and the Guiding Opinions on Building a Modern Environmental Governance System (2020). In light of the increasing stringency of these environmental regulations, policymakers and researchers have become concerned that a "one size fits all" approach will lead to adverse consequences. High-pollution firms often face penalties or must relocate due to stringent environmental controls, potentially allowing low-pollution firms to expand their market share (Dechezlepretre and Sato, 2017). Such changes may strengthen the position of low-pollution firms, but they can also result in reduced overall output, leading to higher product prices and potential losses in social welfare. Overall, environmental regulations may be non-competitively neutral.

Existing research suggests that the impact of environmental regulation on firms can be classified into four key aspects. First,

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regulations may increase business' compliance costs (Cherniwchan and Najjar, 2022). Wang et al. (2019) highlighted that these costs can be passed down the industrial chain by regulated firms. Second, regulations may promote green technology innovation (Popp, 2006; Johnstone et al., 2012). Third, they may influence location decisions. Stricter regulations can lead high-pollution firms to relocate their factories. Cai et al. (2016) observed a trend among such firms to shift pollution from internal provincial zones toward the boundary with neighboring provinces. Wu et al. (2017) discovered that regulated firms were more inclined to establish factories in the western region after the "11th Five-Year Plan" set a 10 % reduction target for sulfur dioxide and chemical oxygen demand, resulting in a westward shift in pollution. Fourth, regulations reallocate resources and production away from pollution-intensive economic activity. Levinson (2009) argued that environmental regulations could decrease production by polluting firms and increase dependence on imports. Liu et al. (2021) suggested that these regulations might also reduce labor demand for high-pollution firms. In the absence of a change in overall market demand, low-pollution firms might assume a larger share of production. Cherniwchan and Najjar (2022) concluded that environmental regulations raise costs for domestic producers, making it more difficult for them to compete in foreign markets with firms who do not face similar policies; therefore, for the most affected manufacturers, regulation reduces export volumes and increases the likelihood of plants ceasing exports. In summary, environmental regulations have the potential to impact operational conditions and competition patterns among regulated firms, thereby potentially influencing prices and market power.

The existing literature lacks a systematic study on the influence of environmental regulation on the market power of firms. Neglecting to consider such an impact could significantly harm societal welfare. To truly understand how environmental regulations impact the market power of firms, as well as the decision-making behaviors among firms under this influence, and to investigate the resulting changes in social welfare under varying degrees of regulation, an in-depth analysis that explicitly models competition is needed.

In this article, we construct a theoretical model and employ numerical simulations to explore the effects of environmental regulation on the output decisions of competing firms with high and low pollution levels. We then analyze potential mechanisms through which environmental regulations influence the market power of these two types of firms and affect overall output. Building upon this foundation, we further investigate the effects of environmental regulation on social welfare. To validate the findings of our theoretical model, we conduct an empirical analysis using comprehensive datasets of Chinese manufacturing firms and prefecture-level cities spanning from 2007 to 2014. In accordance with Berry et al. (2019), we use the price-marginal cost markup as a measure for firm pricing in this study.

This study makes several contributions to the existing literature: First, we offer a comprehensive explanation of how environmental regulations affect the market power of both high- and low-pollution firms by developing a model of a complete information game. We identify the potential mechanism relating regulation to industrial output and pricing. Second, we examine the influence of environmental regulation on social welfare, and we compute welfare losses under different levels of regulation stringency using numerical simulation methods. Our study models emissions allowance trading and endogenizes the allowance price as a function of firms' optimal actions. Finally, this study empirically quantifies the impact of environmental regulation on firms' market power and on welfare. It employs a large dataset encompassing Chinese manufacturing firms and prefecture-level cities, comprising 164,093 effective observations spanning from 2007 to 2014. To address potential endogeneity issues, we used the ventilation coefficient as an instrumental variable and constructed an alternative regulation indicator. Our empirical results largely align with the findings from the theoretical model. The theoretical and empirical outcomes of this study provide valuable insights for designing effective environmental regulation.

The remainder of this paper is structured as follows: Section 2 reviews the literature related to environmental regulations. Section 3 presents and solves our theoretical model and presents numerical simulations conducted using the model. Section 4 outlines the empirical analysis and presents our empirical findings, while Section 5 discusses the implications of the findings and concludes the paper.

2. Literature review

Since the establishment of the United States Environmental Protection Agency (EPA) in 1970, government regulations have increasingly focused on environmental quality, product safety, and workplace safety. Environmental regulations have been a significant topic of discussion and research among economists. As primary sources of pollution emissions, businesses have had to contend with environmental regulation by adjusting practices, making green investments, and even restricting production when needed. This situation underscores the ongoing challenge of balancing economic development with environmental protection.

Neoclassical economics suggests that environmental regulations increase production costs for regulated firms, reducing their competitiveness and negating the positive effects of environmental protection (Ouyang et al., 2020). However, Porter and Linde (1995) challenged this traditional view by arguing that well-designed environmental regulations, such as market-based environmental taxes and pollution emission trading mechanisms, can stimulate technological innovation and improve product quality. These measures can offset the compliance costs associated with environmental regulations and potentially enhance firms' competitiveness in the international market, a concept known as the Porter hypothesis.

Building on trade theory, Copeland and Taylor (2004) proposed the pollution haven hypothesis. This hypothesis suggests that if a country tightens its environmental regulations, regulated firms may relocate to countries with weaker regulations to reduce pollution control costs, turning these countries into pollution havens. Related research, such as Berry et al. (2021), has supported the pollution haven hypothesis by revealing that pollution problems are worsening in developing countries with weaker environmental regulations.

The existing literature relating environmental regulation to interfirm competition builds upon the Porter hypothesis and the pollution haven hypothesis. Studies have focused on technological innovation (Johnstone et al., 2012; Benatti et al., 2024),

Table 1
Competitiveness effect due to the different stringency of environmental regulation.

First-order effect	Second-order effect	Third-order effect			
Cost impacts	Firm responses	Economic outcomes	Environmental outcomes	Technological outcomes	International outcomes
Changes in production costs (direct and indirect costs)	(1) Production volume (2) Product prices (3) Productive investments (4) Investment in abatement	(1) Profitability (2) Employment (3) Market share	(1) Pollution levels and intensity (2) Pollution leakage	(1) Input-saving technologies (2) Process innovation (3) Product innovation (4) Total factor productivity	(1) Trade flows (2) Investment location (3) Foreign direct investment

Note: Organized by Dechezlepretre and Sato (2017).

productivity (Lanoie et al., 2008; Shapiro and Walker, 2018; Wang et al., 2019), trade (Kellenberg, 2009; Shapiro and Walker, 2018), employment (Berman and Bui, 2001; Zhong et al., 2021), and industry location (Lin and Sun, 2016; Wu et al., 2017).

Dechezlepretre and Sato (2017) conducted a comprehensive review of the existing literature on the potential influence of environmental policies on firms, identifying three consecutive effects. As depicted in Table 1, the first-order effect is the impact of regulation on firms' production costs. In response to these changes, the second-order effect occurs as firms adjust their product prices, production volumes, or investment decisions. These responses, in turn, lead to third-order effects, which include economic, environmental, technological, and international outcomes.

In general, studies examining the relationship between environmental regulations and market power have focused on four broad effects. The first is market share expansion by advantaged firms: Certain firms with capital and scale advantages are able to expand their market share through compliance with environmental regulations. These firms voluntarily adopt cleaner technologies, signaling to the government that regulations are not excessive; they may even lobby the government to negatively impact competitors, enhancing their own competitive advantage and profitability (Ehrhart et al., 2008). Stricter regulations can benefit these firms by helping them maintain or increase their market share (Salop and Scheffman, 1983; Dean and Brown, 2017). Additionally, mechanisms such as license trading can promote mergers between firms, improving their market power (Creti and Sanin, 2017).

Second is the effect on market structure: Strengthening environmental regulations can impact the number of firms in the industry. Stringent regulations elevate technical standards and establish entry barriers, posing challenges for new firms attempting to enter the market (Pashigian, 1984; Deily and Gray, 1991). Existing firms may find it necessary to pursue mergers and acquisitions to expand, driven by increased compliance costs, or face the prospect of reduced profits and potential exit from the market (Snyder et al., 2003).

Third is changes in product mix and resource allocation across sectors: Stricter environmental regulations can lead to shifts in product mix, reflecting resource reallocation. Low-pollution firms may benefit from a favorable regulatory environment, attracting resources from high-pollution firms (Levinson, 2009; Shapiro and Walker, 2018).

Fourth is the impact on product prices: The influence of environmental regulation on prices has been examined by a few scholars, but there are inconsistent research conclusions. Some studies suggest that environmental regulations can impact technological innovation, potentially leading to increase or decrease in product prices (De Miguel and Pazó, 2017). Others indicate that regulated firms may reduce production to decrease pollution emissions, resulting in higher product prices (Anand and Giraud-Carrier, 2020).

Existing research on the impact of environmental regulations on firms' market power has two major limitations. Firstly, the literature lacks a systematic exploration of the relationship between environmental regulations and market power. Secondly, few studies analyze price competition as it relates to environmental regulation. Although environmental regulations aim to improve environmental quality and promote social welfare, significant increases in product prices can lead to reductions in consumer surplus, which in turn can impact social welfare. Building on theoretical analysis, this paper empirically examines the impact of environmental regulation on firms' market power as mediated by interfirm competition. Moreover, this study tests the effect of environmental regulation on social welfare.

3. Theoretical model

3.1. Model setup

We consider a cap-and-trade policy, consistent with the Chinese regulatory regime. Assume that the trading price of emission allowance is $r \geq 0$. r is determined by emission cap S; the stricter the environmental regulation (a smaller S), the higher r tends to be. Let s_i be the initial emission allowances allocated to firm i. Firm i can use these emission allowances for its own production or sell $t_i \leq s_i$ units of them in the emission allowance trading market. If $t_i < 0$, firm i purchases emission allowances. Firm i's profit-maximization problem is

$$\max_{q_i, x_i, t_i} \pi_i = q_i p_i - \kappa_0 - q_i \kappa - c_i e q_i x_i^2 + r t_i \tag{1}$$

$$\text{s.t. } 0 \leq x_i \leq 1,\ e q_i (1 - x_i) \leq s_i - t_i,$$

where the decision variables include output quantity (q_i), the emission reduction ratio (x_i), and emission allowance trading quantity (t_i). κ_0 represents the fixed cost of entering this industry, and κ is the marginal cost. p_i is the product price faced by firm i. Parameter $e > 0$ is an industry-specific emission coefficient, which determines the emissions generated by producing 1 unit of output without any emission reduction. In choosing $x_i \in [0,1]$, firm i may improve its equipment and technology to reduce the emissions per unit of output it generates, so the actual emissions are $eq_i(1-x_i)$. Emission reduction is costly: many studies show that for the same firm, the higher the emission reduction ratio (x_i), the more difficult it is to reduce further emissions (Levi and Nault, 2004; Subramanian et al., 2007), so this paper assumes that the total emission reduction cost of $c_i e q_i x_i^2$, with $c_i \geq 0$, is weakly convex.

The government specifies emission cap S. The smaller S is, the stricter the environmental regulation. Smaller S will push up the emission allowance trading price r. The emission allowance of firm i is s_i, of which $e_i q_i (1-x_i)$ units are used for production and t_i units are sold.

At the industry level, emission allowance trading should also meet the following constraints:

$$S = \sum_{i=1}^{n} s_i \geq 0, \text{ and } \sum_{i=1}^{n} t_i = 0, \tag{2}$$

where n is the number of firms that could potentially enter this market. $\sum_{i=1}^{n} s_i = S$ indicates that total emissions must equal the amount specified in the policy; $\sum_{i=1}^{n} t_i = 0$ indicates the transaction constraint: the number of emissions allowances bought must be the same as the number of emissions allowances sold. The initial allowance allocation has little impact on the theoretical conclusions of this study, but it will affect t_i for each firm and the final profit of each firm.

It is essential to consider the strategic interaction between firms to study market-wide equilibrium outcomes. Let $Q \equiv \sum_j q_j$ denote the total quantity of industrial output, and $Q_{-i} \equiv \sum_{j \neq i} q_j$ denote quantity of output across all firms but i. Following the conventional approach in industrial organization, we define the inverse demand function as

$$p_i(q_i; Q_{-i}) = a - bq_i - \gamma b Q_{-i}, \tag{3}$$

where $0 < \gamma < 1$ indicates the degree of product homogeneity. The smaller γ is, the lower the degree of product homogeneity and the higher the degree of product differentiation. When $\gamma = 0$, the products are completely differentiated, and when $\gamma = 1$, the products are perfect substitutes. Both a and b are known parameters greater than zero.

3.2. Market equilibrium

We now solve for the equilibrium strategies of firms as defined by Eqs. (1)-(3). The following assumption is useful:

Assumption 1. $S = \sum_{i=1}^{n} e_i q_i (1 - x_i)$, that is, the emission allowance trading market clears.

Assumption 1 implies that the constraint $eq_i(1-x_i) \leq s_i - t_i$ must be a binding constraint, which means that each firm will use up all its emission allowances (for its own use or sale). We then prove the following proposition:

Proposition 1. *There are three types of solution to the problem of profit maximization of firm i.*

(1) When $r = 0$, the emission cap specified by the government is ineffective:

$$q_i = \frac{a-\kappa}{[2+(n-1)\gamma]b}, \; x_i = 0; \tag{4}$$

(2) When $0 < r \leq 2c_i$, there is an interior solution:

$$q_i = \frac{a - \kappa - \gamma bQ - [1 - r/(4c_i)]re}{(2-\gamma)b}, \; x_i = \frac{r}{2c_i}, \; t_i = s_i - eq_i(1-x_i); \tag{5}$$

(3) When $r > 2c_i$, there is a corner solution:

$$q_i = \frac{a - \kappa - \gamma bQ - c_i e}{(2-\gamma)b}, \; x_i = 1, \; t_i = s_i \tag{6}$$

We also obtain the following corollary:

Corollary 1. *Given $r > 0$, if $c_i > c_j \geq r/2$, then $eq_i(1-x_i)/q_i \geq eq_j(1-x_j)/q_j$. The emissions per unit of output of firm i are greater than that of firm j.*

According to Proposition 1, whether firm i has an interior solution or a corner solution depends on the relative size of r and $2c_i$. If $c_i = c_j$, firms i and j must have the same type of solution. No matter the type of solution the firms have, from Eqs. (5) and (6) we know that $q_i = q_j$, $x_i = x_j$, and $s_i - t_i = s_j - t_j$ so long as $c_i = c_j$. Therefore, we only need to analyze the equilibrium strategies of different types of firms according to their respective c. In other words, q_i, x_i, and t_i can be re-expressed as q_c, x_c, and t_c, respectively.

According to Corollary 1, the emission per unit output of the firm with relatively small c is small, reflecting that firms with small c are "clean". To simplify this model, assume that c follows a random draw from distribution function $G(c)$, and $0 \leq c \leq \bar{c}$. However, as

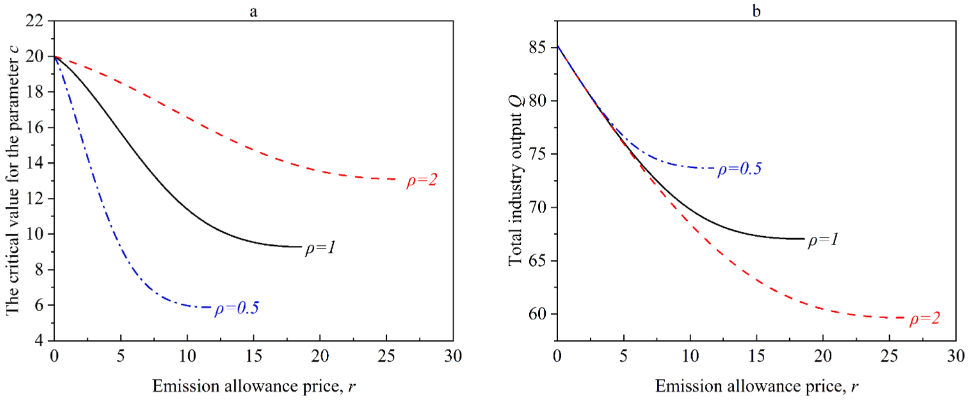

Fig. 1. Environmental regulations and industry output
Note: We adopt the following parameter values: $n = 20$, $e = 1$, $a = 50$, $\kappa = 1$, $\gamma = 0.5$, $b = 1$, $\bar{c} = 20$. As for κ_0, we determine it by solving $\pi_{\bar{c}} = bq_{\bar{c}}^2 - \kappa_0 = 0$. This is because in the absence of environmental regulation, firm $\bar{c}$ can only attain zero profit. ρ taking different values represents firms following different distributions. The critical value of the parameter c is denoted by $\hat{c}$, indicating the threshold at which the firm exits the market. When c exceeds $\hat{c}$, firm c exits the market. In this paper, a higher emission allowance trading price (r) implies stricter environmental regulations. Therefore, the left panel illustrates that, within the given distribution of firms, as environmental regulations become stricter, more firms exit the market. Similarly, the right panel illustrates that, within the given distribution of firms, stricter environmental regulations lead to a decrease in total industry output.

mentioned in introduction section, environmental regulations may lead to some firms exiting the market. According to Proposition 1, $\pi_c = bq_c^2 + rs_c - \kappa_0$, and $\partial \pi_c / \partial c < 0$.[1] Therefore, under a given level of environmental regulations, firms with higher levels of c are more likely to exit the market. Letting $\pi_{\hat{c}} = 0$, we can obtain the condition for firm survival: $c \le \hat{c}(r)$, where $\hat{c} \le \bar{c}$ and $\hat{c}' \le 0$. When $c > \hat{c}$, the corresponding firm exits the market.

We note that the solutions given by Proposition 1 are not the final solutions, because the constraints at the industry level (i.e., Eq. (2)) have not yet been considered. We now consider equilibrium at the industry level. According to Proposition 1, there are two potential scenarios. When $\hat{c} > r/2$, the total quantity of industrial output satisfies

$$Q = \int_{c=r/2}^{c=\hat{c}} \frac{a - \kappa - \gamma bQ - [1 - r/(4c)]re}{(2-\gamma)b} \mathrm{d}nG(c) + \int_{c=0}^{c=r/2} \frac{a - \kappa - \gamma bQ - ce}{(2-\gamma)b} \mathrm{d}nG(c) \tag{7}$$

when $\hat{c} \le r/2$, the total quantity of industrial output satisfies

$$Q = \int_{c=0}^{c=\hat{c}} \frac{a - \kappa - \gamma bQ - ce}{(2-\gamma)b} \mathrm{d}nG(c). \tag{8}$$

According to Proposition 1, when $\hat{c} \le r/2$, all surviving firms achieve a 100 % reduction in emission, indicating extremely stringent environmental regulations. In practice, such a scenario is exceedingly rare, making it reasonable for us to focus solely on the case when $\hat{c}$ exceeds $r/2$. Letting $\hat{r}$ solve $\hat{c}(r) = r/2$, we can obtain the minimum price of emissions, above which all firms reduce their emissions by 100 %. Solving Eq. (7) for Q, online Appendix 2 proves the following proposition.

Proposition 2. *Given Assumption 1 and* $0 \le r < \hat{r}$*, we obtain that* $\partial Q / \partial r < 0$*. Therefore, the stricter the environmental regulations, the lower the industry's total output.*

To illustrate Proposition 2, we perform a numerical simulation analysis. We assume that in the absence of environmental regulation, c follows a power law distribution, that is, $G(c) = c^\rho / \bar{c}^\rho$, $G'(c) = \rho c^{\rho-1} / \bar{c}^\rho$, $0 \le c \le \bar{c}$, $\rho > 0$; Hence, the initial total number of firms is $n = \int_0^{\bar{c}} \mathrm{d}nG(c)$. After considering environmental regulations, due to business exits, the actual number of surviving firms is $\int_0^{\hat{c}} \mathrm{d}nG(c) = nG(\hat{c}) \le n$. Specifically, when $\rho = 1$, c follows a uniform distribution; when $\rho > 1$, there are relatively more firms with a higher emission reduction cost coefficient c; when $0 < \rho < 1$, there are relatively more clean firms with a lower emission reduction cost coefficient c.

Fig. 1a illustrates that, regardless of the specific value of ρ, $\hat{c}'(r) \le 0$. This outcome implies that more stringent environmental

[1] According to China's emission allowance allocation system, $\partial s_c / \partial c \le 0$.

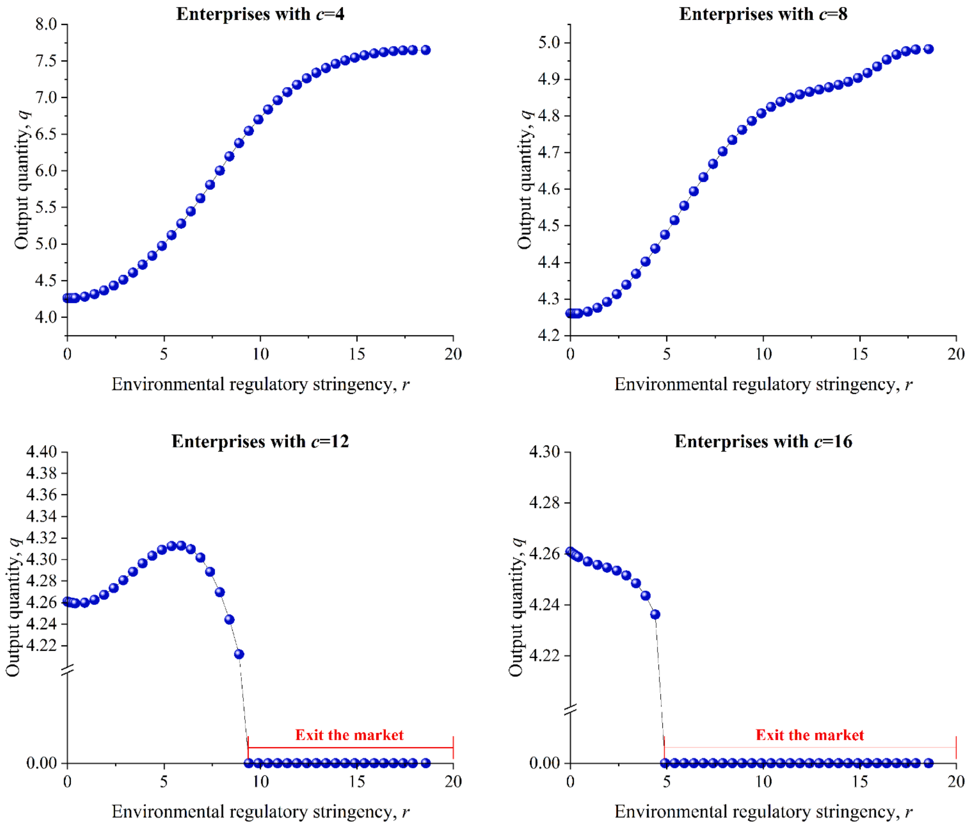

Fig. 2. The changes in firm outputs due to environmental regulations.
Note: During the simulation process, the parameter values adopted are as follows: $n = 20$, $e = 1$, $a = 50$, $\kappa = 1$, $\gamma = 0.5$, $b = 1$, $\bar{c} = 20$. As for κ_0, we determine it by solving $\pi_{\bar{c}} = bq_{\bar{c}}^2 - \kappa_0 = 0$. This is because in the absence of environmental regulation, firm $\bar{c}$ can only attain zero profit. In this paper, a higher emission allowance trading price (r) corresponds to stricter environmental regulations. The coefficient of emission reduction cost, denoted as c, reflects the pollution level of firm c, with higher values indicating greater pollution intensity.

regulations will prompt high-pollution firms to exit the market, thus reducing the average emissions intensity of the market. Moving on to Fig. 1b, it is apparent that, irrespective of the value of ρ, $\partial Q/\partial r < 0$, which means environmental regulations lead to a reduction in the overall industry output, as in Proposition 2. While Proposition 2 focuses solely on the total output of the industry, our primary concern lies in the output changes of individual firms. To address this, we introduce Proposition 3, the proof of which is provided in online Appendix 3. Proposition 3 reveals that while some firms may indeed lower their output in response to environmental regulations, others may conversely increase their production. This finding is consistent with the narrative introduced in our opening, indicating that environmental regulations may favor certain firms.

Proposition 3. *Given the level of $r \in [0, \hat{r})$, there must be a $\tilde{c} \in (r/2, \hat{c})$ such that, when $0 \le c < \tilde{c}$, $\partial q_c/\partial r > 0$; when $\tilde{c} < c \le \hat{c}$, $\partial q_c/\partial r < 0$; and when $c = \tilde{c}$, $\partial q_c/\partial r = 0$.*

By utilizing the simulated data presented in Fig. 1 and assuming $\rho = 1$, we can discern how firms' outputs change when environmental regulations become more stringent, as illustrated in Fig. 2. The simulated results in Fig. 2 exemplify the discoveries outlined in Proposition 3, indicating that environmental regulations can enhance the output of certain firms while diminishing that of others. According to Proposition 3 and Fig. 2, environmental regulations are more likely to reduce the output of high-pollution firms (with higher emission reduction cost coefficients) and increase the output of low-pollution firms (with lower emission reduction cost coefficients).

Another point to note is that, under the cap-and-trade system, government environmental regulations dictate S, not r. Nevertheless, determining S and determining r are essentially equivalent, as S decreases when r increases. Proposition 4 provides a more rigorous statement of this relationship.[2]

Proposition 4. *Let $\bar{S} \equiv n(a-\kappa)e/\{[2+(n-1)\gamma]b\}$. When $0 < S \le \bar{S}$, $\partial r/\partial S < 0$, meaning that, all other factors being equal, a higher emission cap results in a lower transaction price for emission allowances. When $S \ge \bar{S}$ (indicating an ineffective emission cap), $r = 0$. When S*

[2] Please refer to online Appendix 4 for proof.

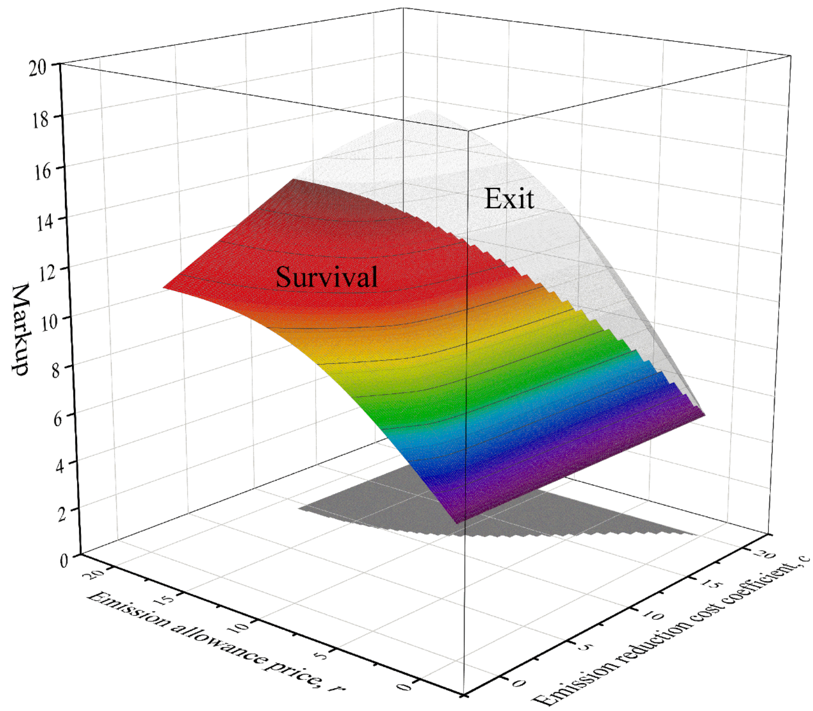

Fig. 3. The changes in firm markups due to environmental regulations.
Note: During the simulation process, the parameter values adopted are as follows: $n = 20$, $e = 1$, $a = 50$, $\kappa = 1$, $\gamma = 0.5$, $b = 1$, $\bar{c} = 20$. As for κ_0, we determine it by solving $\pi_{\bar{c}} = bq_{\bar{c}}^2 - \kappa_0 = 0$. This is because in the absence of environmental regulation, firm $\bar{c}$ can only attain zero profit. The firms in the light-colored area have exited the market. A higher emission allowance trading price (r) corresponds to stricter environmental regulations. The coefficient of emission reduction cost, denoted as c, reflects the pollution level of firm c, with higher values indicating greater pollution intensity.

$= 0$ *(resulting in 100 % emission reduction),* $r = \hat{r}$. *Therefore, the condition* $0 < S \leq \overline{S}$ *is equivalent to* $0 \leq r < \hat{r}$.

Pursuant to Proposition 2, as environmental regulations become more stringent, the overall output of the industry declines. Correspondingly, there is an increase in prices and markups. The following proposition, proved in online Appendix 5, establishes this rigorously.

Proposition 5. *When* $r \in [0, \hat{r})$, *as environmental regulations become more stringent, the price-marginal cost markups of both low-pollution and high-pollution firms increase. However, the markups of high-pollution firms with larger* c *increase at a faster rate.*

Fig. 3 illustrates the findings of Proposition 5: As the stringency of environmental regulation increases, the markups of surviving firms increase, and this increase is more rapid for high-pollution firms with larger c.

All else equal, increasing markups can increase profits. However, once a firm increases its markup, the products of its competitors will be relatively cheap, resulting in a decline in its sales. Of course, the firms can form a cartel organization to jointly improve markups, but it is likely to face antitrust litigation and is unstable. Therefore, in the absence of environmental regulation, the competitive equilibrium will involve markups that are not too high. In the presence of environmental regulation, the firms are forced to reduce industrial output (Proposition 2) and therefore increase their markups (Proposition 5).

3.3. *Welfare analysis*

According to Proposition 5, environmental regulations cause an increase in firms' markups, thus shifting a portion of the costs imposed by environmental regulations onto consumers. This means welfare may be impacted. Before delving into welfare analysis, it's essential to first define social welfare. In our setting, we must consider environmental quality in addition to producer surplus (*PS*) and consumer surplus (*CS*). Some scholars argue that the more emissions there are, the lower the environmental quality, resulting in decreased social welfare. In our study, we assume the welfare loss from emissions is quadratic, leading to a specific formulation of social welfare:

$$W = PS + CS - d\min\{S, \overline{S}\}^2, \tag{9}$$

where $d \geq 0$ is a given parameter, measuring the impact of emission on social welfare. According to Proposition 4, when $S \geq \overline{S}$, the actual emission is equal to $\overline{S}$ because the emission cap is ineffective.

From Proposition 1, we can obtain the following equation:

$$\pi_c = bq_c^2 + rs_c - \kappa_0, c \in [0, \widehat{c}]. \tag{10}$$

Producer surplus is equal to the sum of firm profits :[3]

$$PS = \int_0^{\hat{c}} [bq_c^2 + rs_c]\,\mathrm{d}nG(c) - n\kappa_0 = \int_0^{\hat{c}} (bq_c^2)\,\mathrm{d}nG(c) - n\kappa_0 + rS. \tag{11}$$

According to the definition of consumer surplus and Eq. (3), we obtain

$$CS = \frac{b}{2}\int_0^{\hat{c}} q_c^2\,\mathrm{d}nG(c). \tag{12}$$

Substituting Eqs. (11) and (12) into Eq. (9) yields

$$W = \frac{3b}{2}\int_0^{\hat{c}} q_c^2\,\mathrm{d}nG(c) - n\kappa_0 + rS - d\min\{S, \overline{S}\}^2. \tag{13}$$

Assumption 2. $e[(n-1)\gamma - 1] + \frac{3}{2}\widehat{c}'(0) \geq 0$, which guarantees that $\lim_{r\to 0^+} \partial W/\partial r > 0$.

Assumption 2 implies, first, that the number of firms should not be too small. Second, $\widehat{c}'(0)$ should not be excessively negative, which is generally easy to satisfy. Generally, when environmental regulations are extremely lenient, minor restrictions won't lead to a significant exodus of businesses from the market. If $\widehat{c}'(0)$ is exceedingly negative, even slight environmental regulations will cause numerous businesses to exit the market, making it challenging to enhance social welfare. Third, the emission coefficient e should not be too small. In other words, when e is relatively high, the level of industry pollution is comparatively elevated, which increases the likelihood that environmental regulations enhance social welfare. Overall, satisfying Assumption 2 is not a formidable task. The reason for imposing Assumption 2 is to guarantee that $\lim_{r\to 0^+} \partial W/\partial r > 0$, which can be proved as follows:

In the interval of $S \in [0, \overline{S}]$,

$$\frac{\partial W}{\partial r} = 3b\int_0^{\hat{c}} q_c \frac{\partial q_c}{\partial r}\,\mathrm{d}nG(c) + \left(\frac{3b}{2}q_{\hat{c}}^2\right) nG'(\widehat{c})\widehat{c}' + S + r\frac{\partial S}{\partial r} - 2dS\frac{\partial S}{\partial r},$$

where $\partial S/\partial r < 0$ because of Proposition 4. Hence,

$$\lim_{r\to 0^+}\frac{\partial W}{\partial r} > \lim_{r\to 0^+}\left\{3b\int_0^{\hat{c}} q_c\frac{\partial q_c}{\partial r}\,\mathrm{d}nG(c) + \left(\frac{3b}{2}q_{\hat{c}}^2\right) nG'(\widehat{c})\widehat{c}' + S\right\}.$$

According to Proposition 1, online Appendix 2 and Appendix 3, $\lim_{r\to 0^+} q_c = \frac{a-\kappa}{[2+(n-1)\gamma]b}$, $\lim_{r\to 0^+} Q = \frac{n(a-\kappa)}{[2+(n-1)\gamma]b}$, $\lim_{r\to 0^+} \frac{\partial Q}{\partial r} = -\frac{en}{[2+(n-1)\gamma]b}$, $\lim_{r\to 0^+} \frac{\partial q_c}{\partial r} = \frac{-e}{[2+(n-1)\gamma]b}$. Therefore, given Assumption 2,

$$\lim_{r\to 0^+}\frac{\partial W}{\partial r} > \frac{e[(n-1)\gamma - 1] + \frac{3}{2}\widehat{c}'(0)}{[2+(n-1)\gamma]^2 b} n(a-\kappa) \geq 0.$$

3.3.1. Ignoring the direct impact of environmental quality on social welfare

Since d is a subjective parameter, we temporarily do not consider it. Then the social welfare is

$$W = \frac{3b}{2}\int_0^{\hat{c}} q_c^2\,\mathrm{d}nG(c) - n\kappa_0 + rS. \tag{14}$$

Because W is a continuous function of r, under the conditions of Assumptions 1 and 2, there must exist an $r^* \in (0, \widehat{r}]$, such that the level of social welfare is maximized. In other words, compared to the situation without environmental regulations ($r = 0$), a certain degree of environmental regulation can enhance the level of social welfare.

3.3.2. Considering the direct impact of environmental quality on social welfare

According to Eqs. (13), (14), and Proposition 4, when $0 \leq S \leq \overline{S}$,

[3] The sunk costs of the exiting firms are also taken into account.

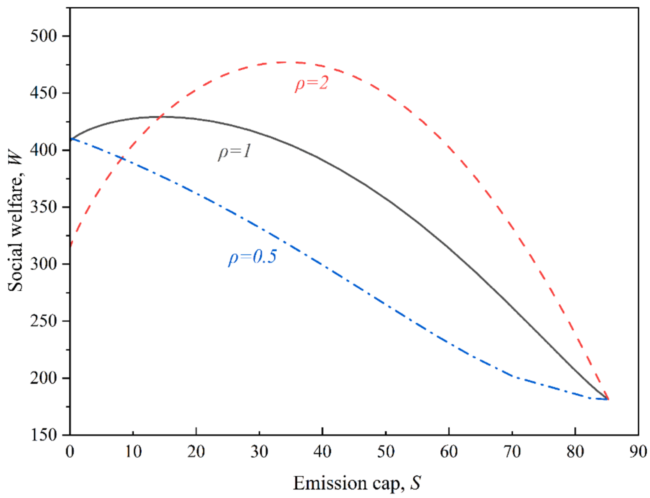

Fig. 4. Environmental regulations and social welfare.
Note: During the simulation process, the parameter values adopted are as follows: $n = 20$, $e = 1$, $a = 50$, $\kappa = 1$, $\gamma = 0.5$, $b = 1$, $\bar{c} = 20$. As for κ_0, we determine it by solving $\pi_{\bar{c}} = bq_{\bar{c}}^2 - \kappa_0 = 0$. This is because in the absence of environmental regulation, firm $\bar{c}$ can only attain zero profit. ρ taking different values represents firms following different distributions. Regarding the initial allocation of emission allowances, in line with the specific circumstances in China, we establish that $s_c = Sq_c/Q$. A smaller emission cap S indicates more stringent environmental regulations.

$$\frac{\partial W}{\partial r}(d>0) - \frac{\partial W}{\partial r}(d=0) = -2dS\frac{\partial S}{\partial r} \geq 0. \tag{15}$$

We have shown that when $d = 0$, there must be $r^* \in (0, \hat{r}]$ that maximizes social welfare. Eq. (15) shows that when $d > 0$, there must be $r^{**} \in (0, \hat{r}]$ that maximizes social welfare and $r^{**} \geq r^*$. When d is large enough, $r^{**} = \hat{r}$ (i.e., $S = 0$), so the strictest possible environmental regulations should be adopted. In other words, whether or not the direct impact of environmental quality on social welfare is considered, there is always an optimal level of environmental regulation in the interval of $r \in (0, \hat{r}]$ (i.e., $S \in [0, \overline{S})$).

Proposition 6. *Under Assumptions 1–2, compared to the situation without environmental regulation, a certain degree of environmental regulation can improve the level of social welfare.*

3.3.3. A simulation analysis

Eq. (13) shows that the relationship between environmental regulations and social welfare depends crucially on the distribution of firm emissions reduction costs $G(c)$. Though Proposition 6 establishes that some degree of environmental regulation is welfare-enhancing, it is challenging to characterize the optimal level of regulation. To shed light on this matter, we conducted a comprehensive numerical simulation analysis utilizing the data presented in Fig. 1. The outcomes are depicted in Fig. 4.

As depicted in Fig. 4, different distributions over c have very different implications for the relationship between the level of regulation and welfare. When $\rho = 2$, social welfare takes on an inverted U-shaped pattern, while for $\rho = 0.5$, social welfare increases as environmental regulations become more stringent. Fig. 4 underscores that, compared to a scenario with no environmental regulation, a certain level of environmental regulation can enhance social welfare (Proposition 6). Furthermore, Fig. 4 shows that an increased presence of low-pollution firms is more likely to lead to environmental regulations enhancing social welfare. It is worth noting that the inverted U-shaped relationship illustrated in Fig. 4 may not necessarily manifest under different distribution conditions. Online Appendix 6 suggests that an M-shaped relationship could even emerge.

3.4. A dynamic extension

The theoretical analysis presented in the preceding section took distribution $G(c)$ as exogenous. In real-world scenarios, firms may be able to diminish their values of c by investing in clean equipment or technology, suggesting the endogeneity of c (Bustos, 2011; Cherniwchan and Najjar, 2022).[4] To tackle this issue, we consider a dynamic model that has three stages: first, the government determines the environmental regulatory stringency indicator S; second, firms decide on the investment φ_i in emission reduction equipment and technology; and finally, firms make determinations regarding the output q_i, emission reduction ratio x_i, and the volume of emission allowance trading t_i. For the sake of simplicity, we restrict our consideration to two types of firms, each associated with distinct emission reduction cost coefficients: c_l and c_h, where $0 \leq c_l < c_h$. Acknowledging that investments in emission reduction

[4] As Cherniwchan and Najjar (2022) mentioned, "environmental regulations require regulated firms to either: (i) adopt leading technologies that lower the emission intensity of production, or (ii) face a regulatory sanction, such as a fine or production quota."

equipment and technology can reduce the emission reduction cost, we therefore let

$$c_i(\varphi_i) = c_l + (c_h - c_l)\left(1 - \frac{\varphi_i}{z_i}\right),\ z_i > 0,\ 0 \le \varphi_i \le z_i. \tag{16}$$

We later will prove that the equilibrium value of φ_i can only be 0 or z_i: when $\varphi_i = 0$, $c_i = c_h$, signifying that firm i abstains from investing in emission reduction equipment and technology, thereby opting for a high-pollution profile; when $\varphi_i = z_i$, $c_i = c_l$, signifying that firm i decides to investing in emission reduction equipment and technology, consequently choosing a low-pollution profile. As firms may have invested in emission reduction equipment and technology, the profit function of Eq. (1) changes to:

$$\max_{q_i, x_i, t_i} \pi_i = q_i p_i - \varphi_i - q_i \kappa - c_i e q_i x_i^2 + r t_i \tag{17}$$

$$\text{s.t. } 0 \le x_i \le 1, e q_i (1 - x_i) \le s_i - t_i,$$

which transforms the original κ_0 into a heterogeneous φ_i. Based on the proof in online Appendix 1, Proposition 1 remains valid. This is evident because we assumed that the decision variable φ_i in the second stage was predetermined when addressing the decision in the third stage.

Given a specific value of r, we can assume there are a total of $n(r)$ firms, comprising $m(r)$ low-pollution firms and $(n(r) - m(r))$ high-pollution firms. According to the condition mentioned in Proposition 1: $0 \le r \le 2c_i$ or $r > 2c_i$, the final solution needs to be discussed in four cases: $r = 0$, $0 < r \le 2c_l$, $2c_l < r \le 2c_h$, and $r > 2c_h$. Under the four cases, online Appendix 7 proved the following proposition.

Proposition 7. *Given Assumptions 1 and 2, let*

$$\underline{S} \equiv (n-m)e\left(1 - \frac{c_l}{c_h}\right)\frac{(a-\kappa)(2-\gamma) + \gamma m c_l e + (-m\gamma - 2 + \gamma)[1 - c_l/(2c_h)]2c_l e}{(2-\gamma)[2+(n-1)\gamma]b},\ \overline{S} \equiv \frac{n(a-\kappa)e}{[2+(n-1)\gamma]b}.$$

(1) When $S \ge \overline{S}$, we obtain that $r = 0$, and the final solution is

$$Q = \frac{(a-\kappa)n}{[2+(n-1)\gamma]b},\ q_l = q_h = \frac{a-\kappa}{[2+(n-1)\gamma]b},\ x_l = x_h = 0.$$

At this time, the environmental regulation is so loose that it does not play any role.

(2) When $\underline{S} \le S < \overline{S}$, we obtain that $0 < r \le 2c_l$, and the final solution is

$$Q = \frac{(a-\kappa)n - m\left(1 - \frac{r}{4c_l}\right)re - (n-m)\left(1 - \frac{r}{4c_h}\right)re}{[2+(n-1)\gamma]b},$$

$$q_l = \frac{(a-\kappa)(2-\gamma) + [\gamma - 2 - (n-m)\gamma]\left(1 - \frac{r}{4c_l}\right)re + (n-m)\gamma\left(1 - \frac{r}{4c_h}\right)re}{(2-\gamma)[2+(n-1)\gamma]b},\quad x_l = \frac{r}{2c_l},$$

$$q_h = \frac{(a-\kappa)(2-\gamma) + \gamma m\left(1 - \frac{r}{4c_l}\right)re + (-m\gamma - 2 + \gamma)\left(1 - \frac{r}{4c_h}\right)re}{(2-\gamma)[2+(n-1)\gamma]b},\ x_h = \frac{r}{2c_h}.$$

Here, the stringency of environmental regulation is moderate. Both low-pollution and high-pollution firms will not sell all their emission allowances.

(3) When $0 \le S < \underline{S}$, we obtain that $2c_l < r \le 2c_h$, and the final solution is

$$Q = \frac{(a-\kappa)n - mc_l e - (n-m)\left(1 - \frac{r}{4c_h}\right)re}{[2+(n-1)\gamma]b},$$

$$q_l = \frac{(a-\kappa)(2-\gamma) + [\gamma - 2 - (n-m)\gamma]c_l e + (n-m)\gamma\left(1 - \frac{r}{4c_h}\right)re}{(2-\gamma)[2+(n-1)\gamma]b},\ x_l = 1,$$

$$q_h = \frac{(a-\kappa)(2-\gamma) + \gamma m c_l e + (-m\gamma - 2 + \gamma)\left(1 - \frac{r}{4c_h}\right)re}{(2-\gamma)[2+(n-1)\gamma]b},\ x_h = \frac{r}{2c_h}.$$

Here, environmental regulation is relatively strict, so that the emission reduction ratio of low-pollution firms reaches 100 % and low-pollution firms will sell all their emission allowances; high-pollution firms may purchase or sell emission allowances based on their initial emission allowances, but at least some high-pollution firms will purchase allowances, otherwise Eq. (2) is not satisfied.

(4) When $S = 0$, we obtain that $r \geq 2c_h$, and the final solution is

$$Q = \frac{(a-\kappa)n - mc_l e - (n-m)c_h e}{[2+(n-1)\gamma]b},$$

$$q_l = \frac{(a-\kappa)(2-\gamma) + [\gamma - 2 - (n-m)\gamma]c_l e + (n-m)\gamma c_h e}{(2-\gamma)[2+(n-1)\gamma]b},\ x_l = 1,$$

$$q_h = \frac{(a-\kappa)(2-\gamma) + \gamma m c_l e + (-m\gamma - 2 + \gamma)c_h e}{(2-\gamma)[2+(n-1)\gamma]b},\ x_h = 1.$$

Here, the environmental regulation is extremely strict, so all businesses reduce their emissions by 100 %.

According to the proof in online Appendix 7, a decrease in S will lead to an increase in r. Therefore, we can describe the tightening of environmental regulation by an increase in r. Based on Proposition 7 and Eq. (17), the profit of firm i is:

$$\pi_i = bq^2_{c_i(\varphi_i)} + rs_{c_i(\varphi_i)} - \varphi_i. \tag{18}$$

In accordance with the actual method of allocating carbon emission allowances in China, we set $s_{c_i(\varphi_i)} = S \cdot \varsigma_{c_i}$, where $\partial\varsigma_{c_i}/\partial q_{c_i} \geq 0$ and $\partial^2\varsigma_{c_i}/\partial q^2_{c_i} = 0$, signifying that firms with higher cleanliness levels receive a larger share of allowances. Using backward induction, under the given conditions of firm output and emission reduction decisions (i.e., Proposition 7), firms determine φ_i by maximizing Eq. (18). The corresponding first-order condition is:

$$2bq_{c_i}\frac{\partial q_{c_i}}{\partial c_i}c_i'(\varphi_i) + rS\frac{\partial\varsigma_{c_i}}{\partial c_i}c_i'(\varphi_i) = 1, \tag{19}$$

where $c_i(\varphi_i)$ satisfies Eq. (16). Furthermore, taking the second derivative of Eq. (18) yields

$$\left[2b\left(\frac{\partial q_{c_i}}{\partial c_i}\right)^2 + 2bq_{c_i}\frac{\partial^2 q_{c_i}}{\partial c_i^2} + rS\frac{\partial^2\varsigma_{c_i}}{\partial c_i^2}\right]c_i'(\varphi_i)^2 + \left[2bq_{c_i}\frac{\partial q_{c_i}}{\partial c_i} + rS\frac{\partial\varsigma_{c_i}}{\partial c_i}\right]c_i''(\varphi_i), \tag{20}$$

where $\partial\varsigma_{c_i}/\partial c_i \leq 0$, $\partial^2\varsigma_{c_i}/\partial c_i^2 \geq 0$, $\partial^2 q_{c_i}/\partial c_i^2 \geq 0$, and $c_i''(\varphi_i) = 0$. Therefore, Eq. (20) is greater than or equal to 0, so the second-order condition is not met, and φ_i is a corner solution. Firm i either does not invest or invests z_i. When $\varphi_i = 0$, $c_i = c_h$ and $\pi_h = bq_h^2 + rs_h$; when $\varphi_i = z_i$, $c_i = c_l$ and $\pi_l = bq_l^2 + rs_l - z_i$.

Given r, if $z_i \geq bq_l^2 - bq_h^2 + r(s_l - s_h)$, then $\varphi_i = 0$, indicating that the firm does not invest, and $c_i = c_h$. If $z_i < bq_l^2 - bq_h^2 + r(s_l - s_h)$, then $\varphi_i = z_i$ and $c_i = c_l$. Firms with $\max\{bq_l^2 + rs_l - z_i, bq_h^2 + rs_h\} < 0$ or $q_h < 0$ exit the market. When r increases by a small amount Δ, some high-pollution firms may choose to invest, thereby transforming into low-pollution firms. The values of z_i for these firms satisfy:

$$z_i \geq bq_l^2(r) - bq_h^2(r) + r[s_l(r) - s_h(r)], \tag{21}$$

$$z_i < bq_l^2(r+\Delta) - bq_h^2(r+\Delta) + (r+\Delta)[s_l(r+\Delta) - s_h(r+\Delta)]. \tag{22}$$

Assuming the distribution function of z_i is $Z(z)$, then,

$$\frac{\partial m(r)}{\partial r} = \int_{bq_l^2(r)-bq_h^2(r)+r[s_l(r)-s_h(r)]}^{bq_l^2(r+\Delta)-bq_h^2(r+\Delta)+(r+\Delta)[s_l(r+\Delta)-s_h(r+\Delta)]} \mathrm{d}n_0 Z(z), \tag{23}$$

where n_0 represents the number of firms when there is no environmental regulation. Assuming that $Z'(z)$ is relatively smooth, then when Δ is very small, $\partial m(r)/\partial r$ is also very small. Meanwhile, in reality, the number of high-pollution firms $(n-m)$ is not negligible. Therefore, $\partial m(r)/\partial r \ll n - m$. Under this condition, we can deduce a conclusion similar to Proposition 2: when $0 \leq r < \hat{r}$ (where $\hat{r} \leq 2c_h$), $\partial Q/\partial r < 0$; when $r > \hat{r}$, all high-pollution firms either exit the market or transform into low-pollution firms.[5] In fact, the decrease in total industry output due to environmental regulations aligns well with empirical evidence in China.

Based on Eq. (3) and Proposition 7, we can conclude that the central finding of this paper remains valid in the presence of investment in clean energy. Specifically, tighter environmental regulations lead to an increase in firms' markups, with high-pollution firms experiencing a more rapid increase in their markups.[6]

Welfare analysis. Similar to Eq. (13), given a specific value of r, the overall social welfare is

[5] See the proof in online Appendix 8.
[6] See the proof in online Appendix 9.

$$W = \frac{3}{2}b\left[m(r)q_l^2 + (n(r) - m(r))q_h^2\right] - \int_0^{\Omega} z\mathrm{d}n_0 Z(z) + rS - d\min\{S, \overline{S}\}^2, \tag{24}$$

where $\Omega \equiv bq_l^2(r) - bq_h^2(r) + r[s_l(r) - s_h(r)]$, and $\int_0^{\Omega} \mathrm{d}n_0 Z(z) = m$. According to the proof in online Appendix 10, under the condition of Assumption 2, $\lim_{r\to 0^+} \partial W/\partial r > 0$ still holds. Therefore, some degree of environmental regulation can improve social welfare.

4. Empirical findings

4.1. Sample and data sources

We use firm-level data sourced from the 'China Industrial Firm Database' and the 'Industrial Firm Pollution Emission Database' and city-level data from the 'China City Statistical Yearbooks.' The study covers the period from 2007 to 2014, excluding the year 2010 due to missing core data in the samples. The sample includes all state-owned firms and non-state-owned firms above a designated size. Following the methodology outlined by Brandt et al. (2012), we conduct cross-database matching. Additionally, we adjust administrative divisions to align with the changes published by the State Council from 2007 to 2014. Given revisions to the 'National Economic Industry Classification' in 1994, 2002, 2011, and 2017, and to ensure consistency, we use four-digit industry codes based on the 2011 industry standard. Finally, adopting the approach used by Brandt et al. (2017), we address issues related to firm mergers, restructuring, cross-industry operations, name changes, and input errors.

To ensure the reliability of the samples, and guided by exclusion criteria from prior studies such as Cai and Liu (2009), Hsieh and Klenow (2009), and Brandt et al. (2012), we implement the following procedures on the matched panel data. We exclude samples with more than 12 open months and adjust observations with zero open months to have 1 open month. We also exclude samples with negative exports or negative capital intensity. We exclude observations with total wages payable less than or equal to 0, with fewer than 8 employees, with industrial output values not exceeding 1, with main business revenue not exceeding 0, with missing data on revenue, with total assets less than current assets or accumulated depreciation less than current depreciation, and with missing or abnormal values for key indicators. We apply a 1 % winsorization on the dataset to further mitigate the potential impact of extreme values. Finally, using the year 2007 as the base period, we use ex-factory price indices of industrial products for each region to adjust industrial output value, main business income, industrial sales output value, intermediate input, operating surplus, and payable value-added tax; we also use fixed asset investment price indices for each region to adjust total assets, total fixed assets, and depreciation of fixed assets, and we use consumer price indices for each region to adjust wages payable and total retail sales of consumer goods.

We specifically focus on key industries highlighted in the "Work Plan for Controlling Greenhouse Gas Emissions during the 12th Five-Year Plan Period." The selected industries include steel, building materials, electricity, coal, petroleum, chemicals, non-ferrous metals, textiles, food, papermaking, and construction. These industries are mandated to study and establish emission standards for greenhouse gases and pollutants per unit of product (service). The two-digit industry codes for these focal industries are as follows: Food Processing Industry (C13); Food Manufacturing Industry (C14); Wine, Beverage, and Refined Tea Manufacturing Industry (C15); Tobacco Products Industry (C16); Textile Industry (C17); Furniture Manufacturing Industry (C21); Paper and Paper Products Industry (C22); Printing and Record Media Reproduction Industry (C23); Petroleum Processing, Coking, and Nuclear Fuel Processing Industry (C25); Chemical Raw Materials and Chemical Products Manufacturing Industry (C26); Pharmaceutical Manufacturing Industry (C27); Chemical Fiber Manufacturing (C28); Non-Metallic Mineral Products Industry (C30); Ferrous Metal Smelting and Rolling Processing Industry (C31); Non-Ferrous Metal Smelting and Rolling Processing Industry (C32); Metal Products Industry (C33).

These industries are specifically targeted because they are known for their relatively high atmospheric pollutant emissions, as indicated by Zhou et al. (2021). After the initial matching of the 'China Industrial Firm Database' and the 'Industrial Firm Pollution Emission Database,' a total of 382,431 observations from the period 2007 to 2014 were obtained. Subsequent data processing, according to the criteria mentioned above, resulted in a reduced sample size of 164,093.

4.2. Variables

4.2.1. Dependent variables: price-marginal cost markup

We define price-marginal cost markup as the ratio of price to marginal cost. We face the challenge that marginal costs are unobserved. Addressing this issue, Hall (1988) introduced an insightful approach for estimating markups based on firms' cost-minimizing behavior, and there have been additional advancements in semi-parametric methods for estimating productions functions using microdata in the years since (Berry et al., 1995; Ackerberg et al., 2015). De Loecker and Warzynski (2012, referred to as DLW) integrated the Hall method with the production function estimation approach, devising a three-step method to estimate markup using firm-level data. This method has gained widespread adoption in various research endeavors (De Loecker et al., 2016; Blonigen and Pierce, 2016; Brandt et al., 2017; De Loecker et al., 2020).

Scholars have highlighted flaws in the DLW three-step method that may lead to significant biases in estimated markups. The primary issues stem from the unavailability of product prices and the inherent unobservability of productivity. Additionally, addressing the potential shortcomings of the DLW method, Traina (2018), Karabarbounis and Neiman (2019), and Raval (2023a, 2023b) have articulated various concerns concerning the definition and adjustment of variable inputs, the selection bias in sample firms, and bias in the estimated production function. They have subsequently proposed alternative estimators. Acknowledging the limitations of the DLW method, this paper opts for the approach put forth by Raval (2023a) for estimating markups.

In accordance with Euler's equation, firm i equates the price of freely-mobile factor j to the marginal revenue generated by the factor. This relationship is formulated as follows:

$$r_i^j = mr_i \frac{\partial y_i}{\partial q_i^j}, \tag{25}$$

where r_i^j denotes the price of factor j utilized by firm i, mr_i signifies the marginal revenue of firm i, y_i represents the output of firm i, and q_i^j denotes the quantity of factor j employed by firm i.

Optimal behavior by firm i implies that marginal revenue mr_i should equal marginal cost mc_i. Consequently, Eq. (25) can be modified to:

$$r_i^j = mc_i \frac{\partial y_i}{\partial q_i^j}. \tag{26}$$

Now, Eq. (26) can be reformulated as

$$q_i^j r_i^j = mc_i y_i \theta_i^j, \tag{27}$$

where $\theta_i^j \equiv \partial \ln y_i / \partial \ln q_i^j$, representing the output elasticity of factor j for firm i. Subsequently, Eq. (27) can be modified to:

$$Markup_i = \frac{p_i}{mc_i} = \frac{\theta_i^j}{q_i^j r_i^j \big/ (p_i y_i)}, \tag{28}$$

where p_i signifies the product price of firm i. Eq. (28) forms the basic thinking underlying the application of the DLW method to estimate price-marginal cost markups ($Markup_i$). Utilizing this formula to estimate $Markup_i$ necessitates the prior estimation of θ_i^j, a task fraught with significant challenges. Estimation of θ_i^j typically requires the economist to assume a functional form for the production function. For instance, many studies assume a transcendental logarithmic production function (De Loecker and Warzynski, 2012). However, this approach may exhibit four notable deficiencies. First, the translog production function entails the estimation of many parameters, some of which may lack statistical significance. The accuracy of any estimate of θ_i^j is compromised if it is based on a noisily estimated production function. Second, estimates of θ_i^j using the translog production function are often negative, resulting in $Markup_i$ estimates below zero. Third, due to the unobservability of product prices and total factor productivity, the estimated output elasticity may represent income elasticity (Bond et al., 2021), leading to potential complications in the application of the DLW method. Fourth, a translog production function allows output elasticities to vary based upon inputs, but they remain a deterministic function of production parameters and inputs with no error term. Thus, the translog estimated output elasticities cannot capture the full degree of heterogeneity in input shares across plants (Raval, 2023b).

In a notable contribution, Raval (2023a) introduces an approach for estimating θ_i^j. Assuming free mobility of all factors, we can derive the total variable cost from Eq. (27):

$$\sum_j q_i^j r_i^j = mc_i y_i \sum_j \theta_i^j. \tag{29}$$

By combining Eq. (27) and Eq. (29), the ratio of these two equations can be expressed as follows:

$$\frac{q_i^j r_i^j}{\sum_j q_i^j r_i^j} = \frac{\theta_i^j}{\sum_j \theta_i^j}. \tag{30}$$

Deng et al. (2022b) indicated that when there are constant returns to scale, $\sum_j \theta_i^j = 1$. Subsequently, incorporating this equation into Eq. (30) yields:

$$\frac{q_i^j r_i^j}{\sum_j q_i^j r_i^j} = \theta_i^j. \tag{31}$$

Building upon Eq. (31), Raval (2023a) emphasized that the cost share of factor j can be employed to estimate θ_i^j. The merits of this method are twofold: Firstly, the derivation process above eliminates the need for a functional form assumption on the production function. Secondly, this method is more practical and ensures that θ_i^j falls within the interval $(0,\ 1)$, preventing outliers in the estimation of $Markup_i$. To further mitigate the influence of random factors, Raval (2023a) groups firms into bins with similar labor augmenting productivities based on the ratio of labor to materials costs. The rationale behind this grouping stems from Raval's (2023a) demonstration, within a general production function framework, that firms sharing a similar labor-to-material costs ratio also have similar output elasticities of factors. Since all variables in the factor expenditure share formula ($r_i^j q_i^j/(p_i y_i)$) are observable and θ_i^j can be estimated, we can estimate the firm-level price-marginal cost markup. As highlighted by Raval (2023b), a potential limitation of this cost share estimator lies in its assumption of constant returns to scale. Given this, in our empirical analysis we control for both firm and industry fixed effects as Edmond et al. (2023) do.

4.2.2. Explanatory variable

Brunel and Levinson (2016) identified five distinct methods to measure the stringency of environmental regulation. These are (1) measures based on private sector abatement costs, (2) direct assessments of regulations, (3) composite indexes, (4) measures based on pollution levels, changes, or energy use, and (5) measures derived from public sector expenditures or enforcement. Early studies commonly utilized the proportion of environmental governance investment to GDP as a metric for environmental regulatory stringency (Gray, 1987; Berman and Bui, 2001; Lanoie et al., 2008). However, this approach is not applicable to this paper due to statistical calibration issues in the 'China City Statistical Yearbook' and the absence of 'environmental governance investment' data after 2011.

In recent years, some scholars have turned to measuring local environmental regulatory stringency by examining the quantity of environmental policies, the number of firms penalized by environmental protection departments, and the count of environmental incidents reported by mainstream news media (Shen et al., 2017; Shao et al., 2020). However, relying on total indicators could lead to the conclusion that larger cities have more stringent regulations. Conversely, using per capita indicators might imply that smaller cities have more rigorous regulations.

Several studies employ composite pollution emission indices (Cole and Elliott, 2003; Zhong et al., 2021; Yan et al., 2023) or composite emission reduction rate indices (Shen et al., 2017; Du et al., 2021) directly for assessing environmental regulatory stringency. In line with Shen et al.'s (2017) approach, this paper standardizes the removal rates of sulfur dioxide and particulate matter in each region.[7]

$$prr_{ijt}^{s} = \left[prr_{ijt} - \min_{i,t}(prr_{ijt})\right] \Big/ \left[\max_{i,t}(prr_{ijt}) - \min_{i,t}(prr_{ijt})\right] \tag{32}$$

where prr_{ijt}^{s} represents the standardized removal rate of emission j in city i in year t, while prr_{ijt} denotes the pre-standardized removal rate. To improve metric accuracy, several studies, such as those conducted by Shen et al. (2017) and Du et al. (2021), calculated the weighted sum of standardized removal rates for different pollutants. The weight assigned to prr_{ijt}^{s} is as follows:

$$w_{ijt} = \frac{pe_{ijt}}{\sum_t \sum_i pe_{ijt}} \Big/ \frac{GIV_{it}}{\sum_t \sum_i GIV_{it}} = \frac{pe_{ijt}}{GIV_{it}} \Big/ \frac{\sum_t \sum_i pe_{ijt}}{\sum_t \sum_i GIV_{it}} \tag{33}$$

where pe_{ijt} represents the emission amount of pollutant j in city i in year t, and GIV_{it} denotes the industrial gross output value of city i in year t. By applying Eqs. (32) and (33), numerous scholars define the environmental regulatory stringency of city i in year t as:

$$\widetilde{ERS}_{it} = \frac{1}{2}\sum_j \left(prr_{ijt}^{s} \cdot w_{ijt}\right) \tag{34}$$

According to Eq. (33), if the emission intensity (pe_{ijt}/GIV_{it}) of a specific pollutant is higher in a particular city, the removal rate of that pollutant is given a greater weight. We argue that this is not reasonable. On one hand, higher emission intensity might result from relatively lenient environmental regulations. On the other hand, cities like Beijing and Shanghai, perceived as having stricter environmental regulations, would exhibit low environmental regulatory stringency under this weighted approach due to their lower pollutant emission intensity.

The core idea of using Eq. (33) to weight Eq. (32) can be roughly understood as follows: the higher the pollutant removal rate per unit of industrial value added, the stricter the environmental regulations. However, this idea has significant limitations: the difficulty and social costs of removing different pollutants in different regions vary significantly. For example, the challenge of removing 10 % of sulfur dioxide cannot be directly compared to removing 10 % of particulate matter, and the removal of 10 % of sulfur dioxide in Beijing cannot be directly compared to the same in Qinghai.

A more precise approach considers emission reduction costs when constructing the index of environmental regulatory stringency. We contend that an indicator reflecting emission reduction costs is the shadow price of pollutants. Building on Färe et al. (2022), this study utilizes the directional distance function method to estimate the shadow prices of different pollutants emitted in various regions and years, denoted as ps_{ijt}. Accordingly, this paper defines the environmental regulatory stringency of city i in year t as:

$$\widetilde{\widetilde{ERS}}_{it} = \sum_j \left(prr_{ijt} \cdot \frac{\widetilde{pe}_{ijt}}{GIV_{it}} \cdot ps_{ijt}\right) \tag{35}$$

where $\widetilde{pe}_{ijt}$ represents the quantity of pollutant j generated in city i in year t. When multiplied by prr_{ijt}, it signifies the removal quantity of pollutant j. Further multiplication by ps_{ijt} yields the cost associated with removing the respective pollutant. In comparison to the

[7] Here, we focus solely on sulfur dioxide and industrial particulate matter removal rates, excluding consideration of industrial wastewater discharge compliance and comprehensive solid waste utilization. The omission is due to the absence of continuous city-level data for these factors during the sample period.

commonly used Eq. (34) in previous literature, the main distinctions in Eq. (35) employed in this paper are as follows: First, Eq. (35) considers the emission reduction costs of different pollutants in various regions. Second, Eq. (35) compares the cost of reducing pollution with the industrial value added, making it a comparison between value quantities. Conversely, Eq. (34) compares the physical quantity of pollution reduction with the value quantity of industrial value added, rendering it less comparable. Third, Eq. (34) standardizes the data before weighting, leading to unclear economic implications, while the economic implication of Eq. (35) is more intuitive.

Finally, to address errors and missing values in the original data, this paper employs a polynomial interpolation to supplement certain pollutant removal data. Additionally, to mitigate the influence of outliers we standardize environmental regulatory stringency as follows:

$$ERS_{it} = [\widetilde{\widetilde{\widetilde{ERS}}}_{it} - \min_{it}(\widetilde{\widetilde{\widetilde{ERS}}}_{it})]/[\max_{it}(\widetilde{\widetilde{\widetilde{ERS}}}_{it}) - \min_{it}(\widetilde{\widetilde{\widetilde{ERS}}}_{it})]. \tag{36}$$

While the environmental regulations discussed in our theoretical model centered on the control of carbon emission, the indicator we construct in this section concerns sulfur dioxide and particulate matter. Several reasons support this treatment. First, China's carbon emission control objectives are predominantly outlined in medium to long-term plans, such as five-year plans and guidelines articulated in documents like the "Opinions on Thoroughly Implementing the New Development Philosophy to Accomplish Peak Carbon Emissions and Carbon Neutrality" issued by the CPC Central Committee and the State Council. Therefore, there are no carbon emissions reduction targets at the individual year-region level. Secondly, burning fossil fuels leads to the emission of many pollutants, including sulfur dioxide, nitrogen oxides, particulate matter, and greenhouse gases such as carbon dioxide (Nam et al., 2014). Because these pollutants and carbon emissions originate from the same sources,[8] regulations targeting one set of pollutants will in turn influence firms' carbon emissions. Thirdly, even though the theoretical model in the above section concentrates on carbon emission control, substituting carbon emissions with SO_2 or other pollutants maintains the validity of our theoretical findings. Finally, to demonstrate the robustness of our empirical examination, we introduce an alternative environmental regulation measurement indicator in subsequent sections.

4.2.3. *Control variables*

In accordance with studies conducted by Zhou et al. (2021), the control variables selected in this paper primarily encompass firm age, ownership, capital intensity, export intensity, salary, size, and total retail sales of consumer goods. We include age because at different lifecycle stages exhibit significant differences in external financing, capital scales, market shares, and government-business relationships. In this paper, the age of a firm = the current year – the year of establishment + (12 – the month of establishment + 1) / 12. Based on different types of ownership, firms can be classified as state-owned or non-state-owned. Political connections may lead to variation in the environmental regulatory costs faced by various firms. When a firm is state-owned, the variable *SOE* takes a value of 1; otherwise, it takes 0. Export intensity reflects the proportion of a firm's sales in both domestic and foreign markets and can indicate, to some extent, the degree of a firm's dependence on foreign trade. This dependence could influence its pricing strategy. Capital intensity can indicate a firm's comparative advantage and reflect its competitiveness and risk resistance. Changes in capital intensity can influence a firm's pricing strategy to some extent. Salary expenses reflect the labor costs of a firm, and moderate wage growth contributes to improving employee efficiency. However, excessive wage increases can raise operating costs, weakening a firm's market competitiveness and affecting its pricing ability. Labor input is used to control for business size. We use the total retail sales of consumer goods as a proxy for the market demand faced by firms in our data. Pricing strategies are dependent on market structure and the nature of competition. Given this, the study incorporates the Herfindahl-Hirschman Index (HHI) at the four-digit industry and city level as one of the control variables.

4.2.4. *Variables used in mechanism analysis*

According to Proposition 2 and Proposition 5 in the theoretical analysis section, an increase in the stringency of environmental regulation leads to a decrease in total output. As a result, product prices and markups rise. To substantiate this transmission mechanism, a subsequent section will investigate the impact of environmental regulation on changes in output.

4.2.5. *Variables employed for categorizing distinct groups*

According to Corollary 1, the empirical section should distinguish between high-pollution firms and low-pollution firms based on carbon emissions per output. However, it is crucial to acknowledge that China has yet to establish a universal and standardized set of criteria for measuring corporate carbon emissions. Existing studies estimated corporate carbon emissions based on the consumption of three primary fossil energy sources: coal, fuel oil, and natural gas. The primary limitation of this method is its reliance on rough estimates. Furthermore, these studies are confined to the years prior to 2010 due to the unavailability of more recent detailed data on the usage of refined fossil energy sources, such as cleaned coal, coke, gasoline, kerosene, diesel, liquefied petroleum gas, refinery gas, and coke oven gas.

[8] In June 2022, the Ministry of Ecology and Environment, the National Development and Reform Commission, and seven other departments jointly released the "Implementation Plan for Synergistic Efficiency Enhancement of Pollution Reduction and Carbon Reduction", which mentioned that environmental pollutants and carbon emissions have highly similar characteristics and are of similar origin. https://www.gov.cn/gongbao/content/2022/content_5707285.htm.

Table 2
The explanations and definitions of all variables.

Types	Variables	Symbols	Definitions
Explained variable	Price-marginal cost markup	*Markup*	$\frac{p_{it}}{mc_{it}}$
Explanatory variable	Environmental regulatory stringency	*ERS*	Measuring the stringency of environmental regulation in different cities and years
Control variables	Firm age	*Age*	ln [the current year – the year started business + (12 – the month started business + 1) / 12]
	Ownership	*SOE*	Equals 1 if the firm's ownership is state-controlled; otherwise, equals 0
	Capital intensity	*Cap*	ln [net fixed assets / main business income]
	Export intensity	*Exp*	Exports / Industrial sales income
	Gross salaries payable	*Salary*	ln [the total amount of wages that the firm should pay to employees in the current year]
	Firm Size	*Size*	ln [the number of people employed]
	Total retail sales of consumer goods	*TRSCG*	ln [the total value of goods sold by retailers to consumers within a certain geographical region in a specific year]
	Herfindahl-Hirschman index	*HHI*	The total of the squared market shares for firms within each industry, where the market shares are determined by the ratio of each firm's revenue to the overall revenue of that industry
Variables used in mechanism analysis	Total output	*Output*	ln [output of the firm]

Note: ln is an abbreviation for the natural logarithmic function.

Table 3
Descriptive statistics.

Variables	Observations	Mean	Std. dev.	Min	Max
Markup	164,093	1.0397	0.1016	0.9093	1.5219
ERS	164,093	0.0435	0.0469	0.0003	0.2828
Age	164,093	2.2012	0.7179	–2.4849	5.2109
SOE	164,093	0.0648	0.2463	0.0000	1.0000
Cap	164,093	0.2627	3.1057	–11.8276	10.0507
Exp	164,093	0.0887	0.2322	0.0000	2.4526
Salary	164,093	8.3023	1.3344	2.6593	16.2134
Size	164,093	5.4920	1.0603	2.0794	11.6190
TRSCG	164,093	18.0087	1.0624	14.2486	20.6864
HHI	164,093	0.0126	0.0246	0.0005	0.7619
Output	164,093	11.6042	1.4349	6.4075	18.9513

Note: The units for *Age* and *Size* are years and people, respectively. *Salary*, *TRSCG*, and *Output* are all measured in thousands of RMB. *Cap* and *Exp* are represented as fractions. *ERS* is standardized, while *SOE* is a dummy variable. To maintain consistency with the subsequent empirical analysis, variables *Age*, *Cap*, *Salary*, *Size*, *TRSCG* and *Output* are presented as logarithmic statistical results.

The previous section mentioned that carbon emissions have similar sources as pollutants such as SO_2. Consequently, in the absence of more precise data for measuring carbon emissions per unit of output from firms, this paper adopts the approach proposed by Deng et al. (2022a). We use sulfur dioxide emissions, nitrogen oxide emissions, particulate matter emissions, and chemical oxygen demand to formulate a comprehensive emission coefficient for firms. The specific calculation method is outlined below:

$$ee_{it} = \frac{1}{4}(ees_{it} + eed_{it} + eec_{it} + een_{it}), \;\; ees_{it} \equiv \frac{so_{it}/GIV_{it}}{\overline{so_t/GIV_t}}, \;\; eed_{it} \equiv \frac{sd_{it}/GIV_{it}}{\overline{sd_t/GIV_t}}$$

$$eec_{it} \equiv \frac{sc_{it}/GIV_{it}}{\overline{sc_t/GIV_t}}, \;\; een_{it} \equiv \frac{sn_{it}/GIV_{it}}{\overline{sn_t/GIV_t}} \tag{37}$$

where so_{it} represents the sulfur dioxide emissions of firm i in year t, sd_{it} represents the particulate matter emissions, sc_{it} represents the chemical oxygen demand, sn_{it} represents the nitrogen oxide emissions, and GIV_{it} represents the total industrial output value of firm i in year t; $\overline{so_t/GIV_t}$, $\overline{sd_t/GIV_t}$, $\overline{sc_t/GIV_t}$, and $\overline{sn_t/GIV_t}$ respectively denote the average sulfur dioxide emission intensity, average particulate matter emission intensity, average chemical oxygen demand intensity, and average nitrogen oxide emission intensity for all sample firms in year t. Firms with a comprehensive emission coefficient (ee_{it}) greater than the annual average are classified as high-pollution, while those with a coefficient less than or equal to the annual average are categorized as low-pollution.

4.3. Model specification

This paper uses microdata of Chinese industrial firms spanning the period from 2007 to 2014, in conjunction with relevant data

Table 4
Environmental regulations and markups: the baseline results.

Variables	(1)	(2)	(3)	(4)	(5)
ERS	0.1014***	0.1022***	0.1023***	0.1055***	0.1047***
	(0.0249)	(0.0248)	(0.0248)	(0.0241)	(0.0240)
Age		0.0023	0.0025	0.0016	0.0016
		(0.0015)	(0.0015)	(0.0015)	(0.0015)
SOE		0.0065	0.0065	0.0059	0.0059
		(0.0042)	(0.0042)	(0.0042)	(0.0042)
Cap			0.0016**	0.0022***	0.0022***
			(0.0008)	(0.0008)	(0.0008)
Exp			0.0014	0.0002	0.0002
			(0.0038)	(0.0036)	(0.0037)
Salary				0.0118***	0.0118***
				(0.0011)	(0.0011)
Size				–0.0021**	–0.0021**
				(0.0010)	(0.0010)
TRSCG					0.0035
					(0.0031)
HHI					–0.0109
					(0.0254)
Constant	1.0364***	1.0307***	1.0301***	0.9446***	0.8814***
	(0.0011)	(0.0037)	(0.0037)	(0.0117)	(0.0566)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	139,027	139,027	139,027	139,027	139,027
Adj. R^2	0.5213	0.5213	0.5214	0.5240	0.5240

Note: The dependent variable is the price-marginal cost markup, with environmental regulatory stringency (*ERS*) as the key explanatory variable. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

from 286 Chinese cities at the prefecture level and above, to empirically investigate the impact of environmental regulatory stringency on the markups of firms. The objective is to validate the primary conclusions derived from the theoretical model. The baseline regression model is outlined as follows:

$$Markup_{ijt} = \beta_0 + \beta_1 ERS_{jt} + \beta X_{ijt} + \lambda_i + \delta_t + \tau_j + \varepsilon_{it} \tag{38}$$

where $Markup_{ijt}$ signifies the markup of firm i in city j for year t. ERS_{jt} denotes the environmental regulatory stringency of city j for year t, with the coefficient β_1 being the focal point of this study. X_{ijt} represents a series of control variables provided in Table 2. λ_i is the individual fixed effect of firm i, δ_t is the time fixed effect, τ_j is the industry fixed effect, and ε_{it} is the error term.

4.4. Descriptive statistics

Table 3 provides a comprehensive summary of the statistical analysis conducted on all variables used in this study. The markup (*Markup*) has an average of 1.0397 and a standard deviation of 0.1016. The variable *ERS* has an average of 0.0435 and a standard deviation of 0.0469. Additionally, more than 6 % of firms in our samples are state-owned firms.

4.5. Baseline results

Table 4 presents the baseline regression results in this study. In column (1), estimates are provided controlling solely for individual, time, and industry fixed effects. Columns (2) to (5) progressively introduce additional control variables. The results consistently reveal that, regardless of the inclusion of control variables in the model, the estimated coefficient of the environmental regulatory stringency (*ERS*) variable remains significantly positive at the 1 % level. This suggests that an increase in environmental regulatory stringency is associated with higher firm markups. On average, during the sample period, as the level of environmental regulatory stringency increases by one unit, markups increase by about 0.1047 units. Consequently, the findings in Table 4 align with Proposition 5. The positive and significant estimated coefficients for *Cap* and *Salary* imply that higher capital intensity and employee salary contribute to elevated markups. Conversely, the negative and significant estimated coefficient for firm size indicates that larger firms have smaller markups. This suggests that a larger firm size does not necessarily translate to greater market dominance but is more likely indicative of an adoption of a strategy characterized by low-profit and high-sales.

To further investigate the impact of environmental regulations on firms with varying pollution levels, this study classifies firms into high-pollution and low-pollution categories based on the methodology in Section 4.2.5. We compute there are 13,457 high-pollution firms, constituting 19.65 %, and 55,032 low-pollution firms, constituting 80.35 %. Table 5 presents the findings on the influence of

Table 5
Environmental regulations and markups: estimated results for high-pollution firms versus low-pollution firms.

Variables	(1) High-pollution	(2) High-pollution	(3) Low-pollution	(4) Low-pollution
ERS	0.1209***	0.1281***	0.0856***	0.0877***
	(0.0445)	(0.0430)	(0.0246)	(0.0232)
Age		0.0039		0.0012
		(0.0026)		(0.0016)
SOE		0.0302***		0.0020
		(0.0097)		(0.0044)
Cap		0.0015		0.0025***
		(0.0016)		(0.0008)
Exp		–0.0001		0.0007
		(0.0107)		(0.0041)
Salary		0.0123***		0.0121***
		(0.0020)		(0.0012)
Size		0.0003		–0.0021**
		(0.0018)		(0.0010)
TRSCG		–0.0050		0.0047
		(0.0085)		(0.0038)
HHI		–0.0396		–0.0017
		(0.0679)		(0.0293)
Constant	1.0330***	1.0068***	1.0382***	0.8593***
	(0.0016)	(0.1529)	(0.0011)	(0.0713)
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Observations	23,500	23,500	108,106	108,106
Adj. R^2	0.5048	0.5081	0.5365	0.5394

Note: The dependent variable is the price-marginal cost markup, with environmental regulatory stringency (*ERS*) as the key explanatory variable. Based on the comprehensive emission coefficient constructed in this paper, the sample firms are divided into two groups: high-pollution firms (columns (1) and (2)) and low-pollution firms (columns (3) and (4)). Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

environmental regulations on the markups of high and low-pollution firms. Columns (1)-(2) illustrate the effect of increased environmental regulatory stringency on the markup of high-pollution firms, while columns (3)-(4) depict the impact on the markup of low-pollution firms. Table 5 reveals that, after accounting for all control variables, the estimated coefficients of *ERS* for both high and low-pollution firms are positive and significant, at 0.1281 and 0.0877. This suggests that heightened environmental regulatory stringency results in an increased markup for both high and low-pollution firms, and the markup increase for high-pollution firms is more pronounced. Consequently, the empirical findings in Table 5 strongly support the conclusion of Proposition 5.

4.6. *Instrumental variable method*

Although baseline regression presented above has controlled for various firm and regional characteristics and fixed effects, endogeneity issues may persist. To address endogeneity, following the approach of Hering and Poncet (2014), this study uses the Ventilation Coefficient (VC) as an instrumental variable for environmental regulation. This choice is motivated by two factors. First, given constant total emissions, cities with smaller ventilation coefficients tend to exhibit higher pollutant concentration levels. Consequently, local governments in these cities are more likely to enforce stricter environmental regulations. Second, the ventilation coefficient, determined by meteorological and geographical conditions, satisfies the exogeneity assumption of instrumental variables. The original data for calculating the ventilation coefficients are sourced from the ERA-Interim database of the European Centre for Medium-Range Weather Forecasts.

Table 6 presents the results of the 2SLS regression. As observed in column (1), the F-statistic in the first-stage regression exceeds 10 and passes a significance test at the 1 % level, indicating that we do not have a weak instrument problem. The estimated coefficient of VC in the first-stage regression is negative and significant, aligning with the expected negative correlation between the ventilation coefficient and the stringency of environmental regulation. The results of the second stage indicate a significant positive impact of environmental regulatory stringency on firm markups, passing a significance test at the 1 % level. This corroborates the findings of the baseline regression, demonstrating that even after addressing endogeneity concerns related to the core explanatory variable, an increase in environmental regulatory stringency will significantly increase firm markups. Using the 2SLS method, as the environmental regulatory stringency increases by one unit, the markup will increase by 0.5689 units. It should be noted that the estimated coefficient of *ERS* in the second stage of the instrumental variable regression is greatly amplified compared to that in the benchmark regression. One possible explanation is that potential endogeneity issues may lead to underestimating the positive effect of environmental regulations on the markups. Another possible explanation, according to Jiang's (2017) research, is that the estimated coefficient in

Table 6
The estimated results of instrumental variable method.

Variables	(1) *ERS* First step	(2) *Markup* Second step
VC	–0.0260***	
	(0.0047)	
Estimated *ERS*		0.5689***
		(0.1438)
Control variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	139,027	139,027
F-test excluded instrument	30.79***	
p-value (F-test)	0.000	
Under-identification		34.228***
p-value (Under-identification)		0.000
Weak identification F-test		30.788***
p-value (Weak identification F-test)		0.000

Note: Column (1) reports the results of the first step from the 2SLS regression, with the dependent variable being environmental regulatory stringency (*ERS*) and the instrumental variable being the ventilation coefficient (*VC*). Additionally, column (2) presents the results of the second step from the 2SLS regression, with the dependent variable being markup and the key explanatory variable being the estimated environmental regulatory stringency. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods) and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

Table 7
The estimated results of heterogeneity analysis.

Variables	(1) Large firms	(2) SMEs	(3) Eastern region	(4) Central region	(5) Western region
ERS	0.0910***	0.1069***	0.0528**	0.1209**	0.2554***
	(0.0277)	(0.0340)	(0.0242)	(0.0550)	(0.0691)
Constant	0.9651***	0.7844***	0.7896***	0.9697***	0.8941***
	(0.0723)	(0.1074)	(0.1477)	(0.0600)	(0.1092)
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	71,344	61,245	89,071	28,163	21,764
Adj. R^2	0.5658	0.4475	0.5252	0.5038	0.5299

Note: SMEs represent small and medium-sized firms. The dependent variable is markup and the key explanatory variable is environmental regulatory stringency (*ERS*). Columns (1) and (2) respectively display the regression results for large-scale firms and SMEs, while columns (3) to (5) show the regression results for samples in the eastern, central, and western regions, respectively. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods) and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

Table 6 may be a Local Average Treatment Effect. That is, the 2SLS method captures only the average treatment effect of a subset of individuals in this sample (i.e., those firms that are sensitive to changes in the ventilation coefficient), rather than the average treatment effect across all individuals.

4.7. Heterogeneity analysis

This section conducts a heterogeneity analysis to examine our conclusions for different subsamples.

Table 8
The estimated results of heterogeneity analysis based on the 2SLS method.

Variables	The second stage				
	(1) Large firms	(2) SMEs	(3) Eastern region	(4) Central region	(5) Western region
ERS	0.5057***	0.5866***	0.3844*	0.4203*	0.9456***
	(0.1528)	(0.2129)	(0.1946)	(0.2417)	(0.2882)
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
First stage F-statistic for excluded instruments	31.51	23.42	11.80	14.06	11.77
P-value: overidentification test	0.0000	0.0000	0.0002	0.0003	0.0017
Observations	71,344	61,245	89,071	28,163	21,764

Note: SMEs represent small and medium-sized firms. The dependent variable is markup. Columns (1) and (2) respectively display the regression results for large-scale firms and SMEs, while columns (3) to (5) show the regression results for samples in the eastern, central, and western regions, respectively. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods), and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

4.7.1. Heterogeneity analysis based on firm size

Firms of different sizes possess unique resources when confronted with environmental regulations. Generally, larger firms, endowed with relatively more resources, can better navigate the heightened stringency of environmental regulation. However, it is an open question whether larger firms' pricing strategies and organization are more adaptable in the face of regulatory changes than smaller firms.

To examine whether there is heterogeneity in the impact of environmental regulations on firms of varying sizes, this study, following the 'Classification Standards for Large, Medium, and Small Industrial Firms,' designates firms with annual sales revenue and total assets both exceeding 50 million RMB as large firms while categorizing the rest as medium and small firms. As evident from the results in columns (1)-(2) of Table 7, the increase in environmental regulatory stringency significantly increases firm markups. Notably, the increase in markups for medium and small-sized firms is slightly larger than the increase in markups for large firms. This could be because smaller firms are more nimble and adaptable in their output and pricing decisions compared to their larger counterparts. Furthermore, in China, large firms contend with more government regulations, which may prompt a more cautious approach to price increases.

4.7.2. Heterogeneity analysis based on regional differences

There are notable geographic disparities in China, encompassing variations in economic development, market competitiveness, and natural resource endowments. We investigate how these differences translate to environmental regulation and firms' responses. Consistent with various studies, this research categorizes the sample into three regional sub-samples: East, Central, and West.

The empirical findings in columns (3)-(5) of Table 7 reveal positive and statistically significant regression coefficients for *ERS* in all of the East, Central, and West regions. However, the environmental regulation impact in the Central and West regions exceeds that in the East. One plausible explanation is that, given the comparatively lower economic development level in the Central and West regions, the cleanliness of local firms is also diminished, leading to a more substantial impact of environmental regulations. Another factor is that firms can offset the influence of environmental regulations by relocating production lines. As environmental regulations intensify, firms in the East region may transfer their production lines to the Central and West regions, thus mitigating the impact of environmental regulations on output.

4.7.3. Heterogeneity analysis based on 2SLS method

The results in columns (1) and (2) of Table 8 clearly indicate that increasingly stringent environmental regulation significantly increases markups. It is noteworthy that, in this heterogeneity analysis, the estimated coefficients of *ERS* for small and medium-sized firms are still slightly higher than those for large firms. The results in columns (3) to (5) show that the *ERS* regression coefficients for the East, Central, and West regions are all positive and statistically significant. Moreover, the impact of environmental regulation in the Central and West regions exceeds that in the East region. In summary, the empirical results in Table 8 are similar to the benchmark regression reported in Table 7, further validating the positive impact of environmental regulation on markups. However, in terms of magnitude, compared to the benchmark regression in Table 7, the estimated coefficients for *ERS* in Table 8 are larger, suggesting that potential endogeneity issues tend to lead to an underestimation of the positive effect of environmental regulation on markups.

Table 9
The estimated results of robustness tests.

Variables	(1) Alternative explanatory variable	(2) Alternative explained variable	(3) Excluding the effects of other policies and events	(4) Excluding the impact of entry and exit	(5) Control for industry specific demand shock	(6) Pilot provinces and cities
ERW	0.7238**					
	(0.3639)					
ERS		0.0430**	0.0891***	0.1118***	0.1023***	0.0801***
		(0.0219)	(0.0282)	(0.0286)	(0.0241)	(0.0297)
Constant	0.8643***	0.9710***	0.8853***	0.9043***	0.8721	0.9193***
	(0.0613)	(0.0563)	(0.0725)	(0.0785)	(0.0568)	(0.0539)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Change to city FE	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Change to industry-year interactive FE	Yes
Observations	131,168	139,027	72,575	100,827	138,992	67,012
Adj. R^2	0.5302	0.5266	0.6173	0.5221	0.5318	0.5401

Note: Column (1) presents estimates where the dependent variable is markup and the key explanatory variable is the frequency ratio of environmental-related words in local government work reports (*ERW*). In column (2), the dependent variable is estimated by the accounting approach. To exclude the impact of other policies and events, column (3) reports results from a 2SLS regression for the period 2011–2014. Column (4) reports results for firms that have continued to exist during the entire sample period to control for the impact of firm entry and exit. Column (5) presents estimates of changing year fixed effect and industry fixed effect to city fixed effect and industry-year interactive fixed effect, and FE refers to the abbreviation of fixed effects. Column (6) displays results based on pilot provinces and cities, such as Jiangsu, Tianjin, Zhejiang, Hubei, Chongqing, Hunan, Inner Mongolia, Hebei, Shaanxi, Henan, and Shanxi. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods), and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

4.8. Robustness tests

To address potential concerns regarding measurement error in the baseline regression and factors such as firm entry and exit, we conduct a series of robustness tests.

First, to assess the robustness of the baseline estimation to the definition of the environmental regulation indicator, we construct an alternative measure of environmental regulatory stringency proposed by Chen et al. (2021). They used the frequency of environmentally related words in local government work reports as a measure of local environmental regulatory stringency (*ERW*). The construction process for this indicator involves the following steps. First, we collect all government work reports from prefecture-level cities for the years 2007–2014. Next, we tokenize the text of government work reports, count the frequency of environmentally related vocabulary, and calculate its proportion of total words. Environmentally related vocabulary includes terms such as “environmental protection”, “pollution control”, “carbon emissions”, “pollution”, “energy consumption”, “emission reduction”, “wastewater discharge”, “ecology”, “green”, “low-carbon”, “chemical oxygen demand”, “sulfur dioxide”, “carbon dioxide”, “PM10”, and “PM2.5”, among others. The results in column (1) of Table 9 indicate that, even after including a series of control variables, the estimated coefficient of *ERW* remains positive significant at the 5 % level.

Second, we test alternative approaches to measuring markups. There are three primary methods for estimating firm-level markups: the accounting approach (Domowitz et al., 1988; De Loecker et al., 2020), the DLW approach (De Loecker and Warzynski, 2012), and the Raval approach (Raval, 2023a, 2023b) used in this paper. Despite its popularity, the DLW approach has several limitations, including underestimation of factor output elasticity, subjectivity in flexible input selection, heavy dependence on production function identification, and data issues (Bond et al., 2021; Hashemi et al., 2022; Raval, 2023b; Jaumandreu and Lopez, 2024). In contrast, the accounting approach, while potentially underestimating markups, correlates better with actual markups, offers more informative results, and better captures inter-industry differences (Martin, 2002; Siotis, 2003). Therefore, we employ the accounting method as alternative to estimate markups. All related data have been deflated. Column 2 of Table 9 presents the regression results indicating that, compared to the baseline regression, the estimated coefficient of the core explanatory variable *ERS* remains positive and significant at the 5 % level, reinforcing the conclusion that stricter environmental regulations significantly increase markups.

Third, we omit specific events from 2007 to 2009 that could impact firm markups. These include the 11th Five-Year Plan, the 2008 financial crisis, and events like the Beijing Olympics. We therefore remove observations from 2007 to 2009 and limit our sample period to the 2011–2014. The results in column (3) of Table 9 indicate that, even after excluding certain observations, the regression results remain positive and pass a significance test at the 1 % level, further affirming the robustness of the baseline conclusions.

Table 10
The estimated results of robustness tests based on 2SLS method.

Variables	The second stage				
	(1) Alternative explained variable	(2) Excluding the effects of other policies and events	(3) Excluding the impact of entry and exit	(4) Control for industry specific demand shock	(5) Pilot provinces and cities
ERS	0.3002***	0.6561***	0.4778***	0.5979***	0.5085**
	(0.1162)	(0.1793)	(0.1515)	(0.1436)	(0.2462)
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Change to city FE	Yes
Industry fixed effect	Yes	Yes	Yes	Change to industry-year interactive FE	Yes
First stage F-statistic for excluded instruments	30.79	25.84	28.07	34.63	12.31
P-value: overidentification test	0.0000	0.0000	0.0000	0.0000	0.0011
Observations	139,027	72,575	100,827	138,992	67,012

Note: In column (1), the dependent variable is calculated by the accounting approach. To exclude the impact of other policies and events, column (2) reports results from a 2SLS regression for the period 2011–2014. Column (3) reports results for firms that have continued to exist during the entire sample period to control for the impact of firm entry and exit. Column (4) presents estimates of changing year fixed effect and industry fixed effect to city fixed effect and industry-year interactive fixed effect, and FE refers to the abbreviation of fixed effects. Column (5) displays results based on pilot provinces and cities, such as Jiangsu, Tianjin, Zhejiang, Hubei, Chongqing, Hunan, Inner Mongolia, Hebei, Shaanxi, Henan, and Shanxi. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods), and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

Fourth, the entry and exit behavior of firms may influence equilibrium prices. To mitigate the potential interference of firm entry and exit, we conduct an additional robustness test that restricts the sample to firms that persist throughout the sample period. As depicted in column (4) of Table 9, the estimated coefficient of *ERS* for continuously existing firms remains significantly positive, confirming the robustness of the regression results even after adjusting for firm entry and exit.

In column (5) of Table 4, the estimated coefficient of *ERS* under the baseline regression is 0.1047; in column (4) of Table 9, the estimated coefficient of *ERS* is 0.1118. This indicates that during the research period, as the level of environmental regulation increased by one unit, the average markup of firms that continued to exist increased by approximately 0.1118 units. This increase in the *ERS* coefficient suggests that firms persisting throughout the sample period possess greater adaptability to environmental regulation. This adaptation enables these firms to boost their markup more efficiently when confronted with stricter environmental regulations.

Fifth, a possible concern is that industry-specific demand shocks also interfere with the results. To further control for the influence of unobservable factors that vary over time at the industry level, column (5) of Table 9 includes an interaction term between year and industry. The coefficient of *ERS* is still positive and statistically significant at the 1 % level, indicating that the main result of this study is robust.

Last, China's emission trading institution originated from the emission rights permit system in 1988. Per this system, the government transfers emission rights to polluters for a fee and allows these rights to be traded on the secondary market. In 2002, China launched a pilot program for sulfur dioxide emission trading, selecting four provinces (Shanxi, Shandong, Henan, and Jiangsu) and three cities (Tianjin, Liuzhou, and Shanghai) as the initial pilot sites. The subsequent inclusion of Huaneng Group constructed the "4 + 3 + 1″ pilot form. In 2007, the scope of the pilot program was further expanded to cover 11 provinces and municipalities, including Jiangsu, Tianjin, Zhejiang, Hubei, Chongqing, Hunan, Inner Mongolia, Hebei, Shaanxi, Henan, and Shanxi. Since the research period of this paper spans from 2007 to 2014, we limit the scope in a robustness test to the 11 pilot provinces and municipalities. According to the results in column (6) of Table 9, the estimated coefficient of *ERS* remains significantly positive.

Furthermore, to address potential endogeneity issues in the robustness analysis section, this study also provides the results of the second stage using the 2SLS method. Notably, all regression results on *ERS* reported in Table 10 are highly consistent with the baseline results presented in Table 9.

4.9. Mechanism analysis

The theoretical analysis in the preceding sections suggests that the conclusion of environmental regulations leading to an increase in firm markups is primarily due to firms passing on the costs of regulations to downstream consumers through price increases (Proposition 5). Proposition 2 emphasizes that this phenomenon is the consequence of environmental regulations reducing overall industry output, resulting in higher product prices and ultimately leading to an increase in markups. This section empirically tests this

Table 11
The estimated results of mechanism analysis.

Variables	(1) Output	(2) Output of high-pollution firms	(3) Output of low-pollution firms
ERS	–0.5855*	–0.8622***	–0.4038
	(0.3170)	(0.2284)	(0.3358)
Constant	7.6161***	7.6387***	7.9391***
	(1.4064)	(1.2384)	(1.6099)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Observations	139,027	23,500	108,106
Adj. R^2	0.9384	0.9459	0.9430

Note: Column (1) reports results from a 2SLS regression where the dependent variable is firm output and the key explanatory variable is environmental regulatory stringency (*ERS*). Columns (2) and (3) further present the estimates of high-pollution and low-pollution firms, respectively. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods), and *HHI* (Herfindahl-Hirschman index). Among them, variables Age, Cap, Salary, Size, and TRSCG are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

mechanism by estimating the following regression:

$$Output_{it} = \beta_0 + \beta_1 ERS_{jt} + \beta X_{ijt} + \lambda_i + \delta_t + \tau_j + \varepsilon_{it} \tag{39}$$

where $Output_{it}$ is the output of firm i in year t and is expressed in logarithmic form.

Column (1) of Table11 reveals the impact of environmental regulation on firm output. The regression results indicate a notable average reduction in firm output, around 58.55 %, in response to a one-unit increase in environmental regulatory stringency. These findings suggest that stronger environmental regulations reduce overall output, with a potentially greater decrease when considering firm exits. Further, Proposition 3 posits that environmental regulations are more likely to diminish the output of high-pollution firms rather than low-pollution ones. To investigate further, the study classifies sample firms into two sub-samples based on the previously constructed comprehensive emission coefficient.

The empirical results in columns (2) and (3) of Table 11 show that the estimated coefficient of *ERS* for the high-pollution firm sub-sample is –0.8622, passing a significance test at the 1 % level. In contrast, the estimated coefficient for the low-pollution firm sub-sample is –0.4038, failing to pass the significance test at the 10 % level. This indicates that an increase in environmental regulatory stringency results in a significant decline in output for high-pollution firms relative to low-pollution firms. If demand remains unchanged, low-pollution firms may gradually fill the market supply gap caused by the reduced production of high-pollution firms, thereby increasing their market shares.

4.10. An extended analysis of welfare loss

Proposition 6 in Section 3 suggests that a certain degree of environmental regulation can contribute to the enhancement of social welfare. This is attributed to the fact that, under specific environmental regulations, the growth in producer surplus surpasses the decline in consumer surplus. Now, considering the practical scenario in China, has environmental regulation really improved social welfare? This section will conduct an extended empirical examination to address this question. We can assess welfare losses using the following equation:

$$WL_{ij} = -\frac{1}{2}\frac{\partial q_{ij}}{\partial p_{ij}}\left(\Delta p_{ij}\right)^2, \tag{40}$$

where WL_{ij} represents the welfare losses caused by firm i in industry j; p and q signify price and consumption of the product, respectively (Harberger, 1954; Lavergne et al., 2001). Consequently,

$$WL_{ij} = -\frac{1}{2}\frac{\partial \ln q_{ij}}{\partial \ln p_{ij}} p_{ij} q_{ij}\left(\frac{\Delta p_{ij}}{p_{ij}}\right)^2 = -\frac{1}{2} p_{ij} q_{ij} {u_{ij}}^2 \eta_{ij} = -\frac{1}{2} R_{ij} {u_{ij}}^2 \eta_{ij}, \tag{41}$$

where $\eta_{ij} = \frac{\partial \ln q_{ij}}{\partial \ln p_{ij}}$ is the price elasticity of demand, $R_{ij} = p_{ij} q_{ij}$ is the sales revenue of firm i in industry j, $u_{ij} = \frac{\Delta p_{ij}}{p_{ij}} = 1 - 1/\mu_{ij}$ is firm i's market power measured by the Lerner index, and μ_{ij} is the markup estimated above. In the light of the Lerner equation, $\eta_{ij} = -\frac{1}{u_{ij}}$. Then,

$$WL_{ij} = \frac{1}{2} R_{ij} u_{ij}. \tag{42}$$

Table 12
Regression results on welfare loss.

Variables	(1)	(2)
ERS	–1.3807**	–1.3240**
	(0.6455)	(0.6301)
Constant	0.8849***	–3.0253
	(0. 0278)	(1.9162)
Control variables	No	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Observations	139,027	139,027
Adj. R^2	0.6544	0.6586

Note: The logarithm of the welfare loss is the dependent variable, and environmental regulatory stringency (*ERS*) is the key explanatory variable. The control variables include *Age* (firm age), *SOE* (ownership), *Cap* (capital intensity), *Exp* (export intensity), *Salary* (gross salaries payable), *Size* (firm size), *TRSCG* (total retail sales of consumer goods), and *HHI* (Herfindahl-Hirschman index). Among them, variables *Age*, *Cap*, *Salary*, *Size*, and *TRSCG* are in logarithmic form. Time fixed effects are included at the year level, while firm fixed effects are identified by their exclusive ID. Industry fixed effects are based on four-digit industry codes. Standard errors, clustered at the city level, are reported in parentheses. Significance levels are indicated as follows: *** Significant at the 1 % level, ** Significant at the 5 % level, * Significant at the 10 % level.

We do not consider the fixed costs of emission reduction in Eq. (42), nor do we consider the direct effect of environmental improvement, which is denoted as d in the theoretical model. Theoretically, the fixed costs imposed on firms as a result of environmental regulations should be outweighed by the direct welfare gains achieved through environmental improvement. Otherwise, the government would not have implemented stringent environmental regulations after comprehensive consideration.

To ascertain the impact of more stringent environmental regulation on firms' welfare, we test the following model:

$$\ln WL_{ijt} = \beta_0 + \beta_1 ERS_{jt} + \beta X_{ijt} + \lambda_i + \delta_t + \tau_j + \varepsilon_{it}. \tag{43}$$

where X_{ijt} indicates control variables.

Table 12 shows the baseline regression results without and with the introduction of control variables. It is worth noting that the estimated coefficients of *ERS* in columns (1) and (2) are both negative and have passed the significance test at the 5 % level. This indicates that increasing the strictness of environmental regulation can significantly reduce welfare losses at a significance level of 5 %. Specifically, a coefficient of –1.324 indicates that a 1 percentage point increase in environmental regulation intensity results in a roughly 1.324 % decrease in social welfare losses. In other words, the strengthening of environmental regulatory stringency contributes, to some extent, to the increase in social welfare. This suggests that, despite the potential adverse effects of strengthened environmental regulations—such as rising product prices and cost over-shifting—social welfare in the context of China tends to improve with increased environmental regulatory stringency. This confirms the theoretical findings of Proposition 6.

5. Conclusion

This paper offers theoretical and empirical insights into the impact of environmental regulation on firms' market power. The specific theoretical findings are as follows: Stricter environmental regulations diminish the output of high-pollution firms, consequently reducing the industry's total output, while the output of low-pollution firms may increase. As a result of the reduction in the industry's total output, the supply curves shift upwards, leading to an escalation in product prices and a subsequent rise in price-marginal cost markups. Nonetheless, an appropriate stringency of environmental regulation leads to an enhancement in social welfare.

Building on theoretical research and leveraging extensive data from Chinese manufacturing firms spanning 2007 to 2014, this study empirically tests the relationship between environmental regulatory stringency and the price-marginal cost markups of firms. The empirical results indicate that an increase in environmental regulatory stringency significantly increases markups, with the markup growth of high-pollution firms being greater than that of low-pollution firms. Stricter environmental regulations cause firms to decrease the total output of the industry, thereby increasing their markups. Further empirical research has found that a moderate increase in environmental regulatory stringency might contribute to improving the level of social welfare.

This study is subject to several limitations. First, our theoretical model does not consider uncertainty or asymmetric information, particularly in regard to the market for trading emission allowances. Borenstein et al. (2019) offer valuable insights into this aspect. Additionally, environmental regulations in China involve additional measures not captured in this paper, such as mandatory relocation, carbon taxes, and direct administrative penalties. Future research should contemplate the incorporation of these factors.

CRediT authorship contribution statement

Ruizhi Pang: Conceptualization, Supervision. **Xuping Zhang:** Data curation, Writing – original draft. **Matthew Leisten:** Writing – review & editing. **Zhongqi Deng:** Methodology, Formal analysis, Visualization.

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Supplementary materials

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Data availability

Data will be made available on request.

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