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Rivalry signal transmission, technology spillover and corporate environmental performance

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ABSTRACT

We investigate how the Rivalry Signal (RS) and Technology Spillover (TS) affect Corporate Environmental Performance (CEP) through Corporate Environmental Management (CEM). We identify Rival Signal and Technology Spillover from firms' information exchange with their rivals in export networks by product-level data of China based on product space theory. RS indicates intensified competition in a market, and TS indicates useful information in that market. We then explore the effects of RS and TS on CEP, and the empirical results show that RS and TS improve CEP simultaneously. These effects are more pronounced for firms with larger sizes, regions with more severe pollution and coastal areas. By employing mediating effect model, we find that the RS promotes firms' technological improvements and broadens the range of firms' imported intermediates, thereby enhancing CEP; the TS motivates firms to switch to the market's core product and brings about technological improvements, subsequently improving CEP.

1. Introduction

Although the rivals' behavior significantly impacts firms' corporate management strategy and corresponding performance (Porter, 1998), few studies examine the effects of the firms' interaction with business rivals on corporate environmental performance. A rival's efforts offer dual insights: a market rivalry signal, suggesting increased competition, and a technological signal, hinting at a potential technology development within the market (Bloom et al., 2013; Kao, 2024; Markou et al., 2023). These two opposing rival signals operate simultaneously but differently on corporate performance; however, they are hard to be identified, resulting in a dearth of studies that ascertain their influences on corporate performance.

To fill this gap, this paper explores how two opposing effects stemming from firms' information exchange with their rivals - Rivalry Singal (*RS*) and Technology Spillover (*TS*) - affect Corporate Environmental Performance (*CEP*) and how they influence *CEP* through Corporate Environmental Management (*CEM*). The Rivalry Signal (*RS*) indicates potentially heightened competition in that market, while the Technology Spillover (*TS*) suggests possible solutions to a problem in production through information learning and sharing in a market (Bloom et al., 2013; Markou et al., 2023; Rathee et al., 2025; Tao et al., 2024). This paper innovatively constructs indicators

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representing *RS* and *TS* based on firms' information exchange with their market rivals in export networks using social network analysis methods. Additionally, this paper explores the effects of *RS* and *TS* on Corporate Environmental Performance (*CEP*) and how the *RS* and *TS* affect CEP by Corporate Environmental Management (*CEM*) (Xue et al., 2020; Zhou, 2023), including corporate product strategy, technology strategy, and supply chain strategy.

Compared to the previous literature, the present study offers four unique contributions in addition to compiling unique databases. This study is among the first to examine two distinct effects arising from firms' information exchange with their rivals, namely, *RS* and *TS*, on Corporate Environmental Performance. Information sharing and leaking reduce information asymmetry among firms, thereby escalating firms' product imitation and commercial theft (Bloom et al., 2013; Runge et al., 2021; Liang, 2023; Markou et al., 2023). In response to this intensified competition (Skilton & Bernardes, 2015), firms are compelled to enhance corporate supply chain management (i.e., import higher quality intermediate inputs) and promote technological improvements, which we refer to as the Rivalry Signal Effect in this paper. In contrast, the information exchange with business rivals leads to technology spillover, which enhances firms' understanding and technology of specific products and facilitates firms' product switching (Barrows & Ollivier, 2018; Dong & Yu, 2021; Lucking et al., 2018), which we define as the Technology Spillover Effect. It is worth noting that the Rivalry Signal and Technology spillover are accompanying effects and should be considered simultaneously in the empirical estimation. Therefore, previous studies related to the **Pollution Halo Hypothesis**,[2] which emphasize the one-sided effect of technology and neglect the Market Rivalry Effect, likely overestimate the Technology Spillover Effect.

Second, this paper contributes to the literature on the traditional SCP (Structure-Conduct-Performance) paradigm by emphasizing firms' use of information. The majority of literature based on the SCP paradigm primarily focuses on examining the influence of market competition on firm's behavior and performance (Lartey et al., 2023), while overlooking the significance of information. In constrast, this paper shows why intense market competition promotes firm performance from the perspective of information utilization. The more similar the production structure between firms and their rivals, the more intense the market competition between firms, but the more efficiently firms utilize the information. Specifically, being familiar with the production information of their rivals, firms are able to obtain useful information from their rivals' production information faster and more acutely, as is the case with firms' product switch and expansion of intermediate inputs in this study.

The third contribution of this study is to further explore the impact of *RS* and *TS* on *CEP* through Corporate Environmental Management (*CEM*), including product selection, technology & innovation, and the supply chain strategy. *CEM* refers to the strategic and systematic approach that firms adopt to improve overall Corporate Environmental Performance, extending from internal production activities to the consumption of an organization's products or services (Castro et al., 2016; Xue, 2020; Zhou, 2023). Product selection (Yu et al., 2022), technology & innovation (Hao et al., 2022), and supply chain management (Hettler & Graf-Vlachy, 2023) are key points concerning firms' internal production in *CEM*. However, few studies have explored how rival signals affect firms' carbon management concerning these key points. This paper elucidates how *RS* and *TS* affect *CEM*.

The fourth contribution of this paper is to develop two firm-level measurements to identify Rivalry Singal and Technology Spillover from firms' information exchange with their market rivals based on product space theory (Hidalgo et al., 2007). Bloom et al. (2013) identify the *Technology Spillover Effect* (*Market Rivalry Effect*) based on the similarity of firms' product structure in terms of sales (innovation). However, this paper deviates from this prior work by constructing the *TS* based on product similarity (the similarity of production technology) instead of the aggregate firm-level structure, which would be more granular and better capture technology spillover from firms' competitors (Markou et al., 2023). Moreover, this paper is the first to identify *RS* and *TS* from the information exchange in firms' export networks.

The rest of this paper is arranged as follows. Section 2 is the literature review and hypothesis development. Section 3 introduces the empirical methods and data description. Section 4 provides the baseline results, robustness test and the heterogeneity analysis. Sections 5 provide and the mechanism analysis. Sections 6 is the further analysis. The last section presents the conclusion and implications.

2. Literature review and hypotheses development

2.1. Literature review

This paper relates with the literature that delves into the influence of rival behavior on corporate business behavior and strategy. Empirical evidence suggests that rivalry among firms significantly shapes their R&D endeavors and innovation. Bloom et al. (2013) have concurrently assessed the impact of Technology Spillover and Market Rivalry on firm innovation within a unified framework. In a similar vein, Lucking et al. (2018) and Runge et al. (2022) have each explored the distinct influences of Technology Spillover and Market Rivalry on firm R&D initiatives. Tao et al. (2024), leveraging data from 109 Chinese A-share listed high-tech firms spanning from 2013 to 2022, demonstrates that venture capital (VC) syndication networks substantially enhance firms' ability to learn from the failures of their peers, consequently boosting the success rate of exploitative innovations.

Beyond innovation, rival behavior also influences a range of other business behaviors and strategies. Rathee et al. (2025), drawing on data from pharmaceutical companies, probe the effects of competitive pressures on firms' discretionary actions in complying with mandatory R&D disclosures. Their findings indicate that firms are more likely to promptly disclose their R&D outcomes in the face of

[2] Some literature on trade and the environment (Hille et al., 2019; Sudsawasd et al., 2019; Caetano et al., 2022) argue that *FDI* and trade do not deteriorate but rather improve the environmental quality of host countries, which became known as **Pollution Halo Hypothesis**.

fierce competition. Kao (2024), focusing on pharmaceutical companies as well, scrutinizes the role of competitive dynamics in shaping the voluntary disclosure of product quality information by innovative firms. This study reveals that an escalation in market rivalry, signified by the approval of a competitor's drug, decreases the probability of a firm reporting its clinical trial results by 13%. This suggests that firms may strategically withhold information to preserve their competitive edge following the approval of a rival's drug.

This paper addresses a gap in the literature by examining the impact of Rivalry Signal (*RS*) and Technology Spillover (*TS*) on Corporate Environmental Performance (*CEP*), an area unexplored by the aforementioned studies. While existing research focuses on *RS* or *TS* in isolation, neglecting their simultaneous effects can result in omitted variable bias and statistical errors. Although Bloom et al. (2013) concurrently recognize *RS* and *TS*, their study is based on firm-level data. This paper leverages product-level data and the product network approach, providing a broader and more detailed perspective for identifying *RS* and *TS*.

Markou et al. (2023) is the most closely related to our research by examining the effects of *RS* and *TS* on the drug development processes of the top 15 pharmaceutical companies from 1999 to 2016. However, their study differs from ours in three significant respects: firstly, it focuses on R&D behavior rather than environmental performance; secondly, it is limited to large pharmaceutical firms; and thirdly, it identifies *RS* and *TS* based on the number of rival drug-indication projects by sales, without utilizing network analysis to capture the interactive information exchange between firms. In contrast, this paper introduces a novel approach by identifying *RS* and *TS* from information exchange within firms' export networks across a broad sample of exporters, providing a comprehensive analysis of their impact on corporate environmental performance.

2.2. Hypotheses development

(1) Information Exchange and CEP: Market Rivalry Signal and Technology Spillover

Rival Signal may improve Corporate Environmental Performance through two channels, i.e., Rivalry Signal and Technology Spillover. For the *RS*, information sharing reduces information asymmetries among trading agents and intensifies competition among firms as competitive rivals acquire more production technology and market knowledge (Markou et al., 2023; Skilton & Bernardes, 2015). Intensified competition compels firms to enhance their supply chain management (i.e. import more advanced intermediate inputs with higher quality to produce cleaner products) and may also force the enhancement of corporate green innovation (Krass et al., 2013; Sohn, 2008). For the *TS*, information learning can improve firms' technology and promote green innovation, thereby promoting *CEP*. Information sharing could also faciliate firms' product switch to more sustainable products (Barrows & Ollivier, 2018; Dong & Yu, 2021).

Moreover, the *RS* and *TS* represent two dimensions of rival signals, and they should be considered simultaneously in the estimated model to obtain an unbiased effect of rival signals on *CEP*. The omission of the critical explanatory variable Rivalry Signal tends to overestimate the effect of Technology Spillovers in the traditional trade-enviroment literature. We propose Hypothesis 1.

Hypothesis 1. *RS* and *TS* significantly improve *CEP* simultaneously.

(2) How rival singals affect Corporate Environmental management **(***CEM***)**

RS emphasizes that market information sharing about factor supply and product demand can intensify competition among firms. In contrast, *TS* focuses on enhancing firms' production technology through information learning and their more comprehensive understanding of export markets through information sharing. Thus, *RS* and *TS* may have distinct influences on *CEM*.

This section analyses the impact of *RS* and *TS* on *CEM* concerning production in three different ways: "Product Switch", "Technology and Innovation", and "Supply Chain Management". We will also introduce the corresponding hypotheses, illustrated in Fig. 1.

2.2.1. CEM I: Product switch

The exchange of information and technology spillovers in export networks enable firms to have a more timely and comprehensive view of the overall market's product supply, thus prompting them to switch to products that are more favorable to firms' business

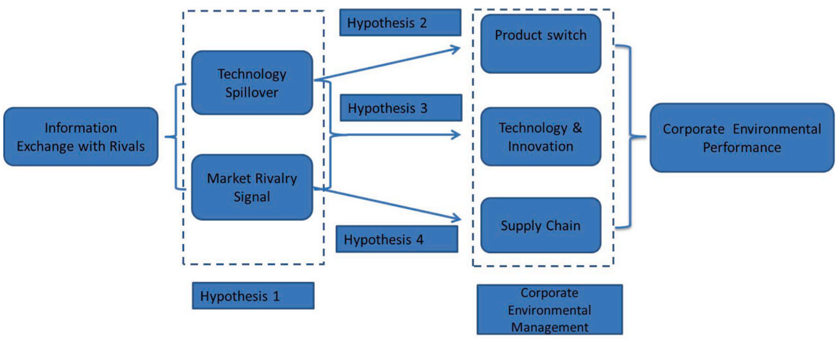

Fig. 1. Influence of *RS* and *TS* on *CEP* and *CEM*.

performance. Literature finds that firms' overall emission intensity can be influenced by product switching and changes in their product mix, as different products have varying emission intensities (Barrows & Ollivier, 2018; Dong & Yu, 2021). Based on data from Indian manufacturing firms, Barrows and Ollivier (2018) observe a negative correlation between pollution emission intensity and the proportion of a firm's main product, contributing the largest share to its output. Similarly, Dong and Yu (2021), utilizing export data from Chinese manufacturing companies, discovered that dedicating more resources to products that closely align with the market's core offerings—those identified by Hidalgo et al. (2007) as having the highest similarity to all other products within the product space—enables firms to gain more valuable insights for enhancing product quality and *CEP*. Consequently, we propose Hypothesis 2.

Hypothesis 2. *TS* promote firms' product switching to the market's core product, which improves *CEP*.

2.2.2. CEM II: Technology and innovation

The existing literature confirms the positive role of technology spillovers brought by external factors (i.e. trade and *FDI*) in promoting firms to adopt more environmentally friendly production technologies (Jing & Zhang, 2014). The development and expansion of export networks provide more channels for Knowledge Spillovers (Chaney, 2014, 2016; Garmendia et al., 2012; Rauch, 1999, 2001), and increase the information spillovers across products (Yu et al., 2023), enabling firms to acquire more advanced technologies and implement technology upgrades to improve corporate environmental performance. Markou et al. (2023) also verify the positive role of technology spillover in developing new drugs. Moreover, inter-enterprise rivalry compels enterprises to intensify R&D investments, innovation, and technological advancements to bolster their competitive edge. Aligning with the Porter Hypothesis, firms can achieve excellence amidst intense competition and environmental pressures by more vigorously pursuing green R&D and technological collaboration (Aghion et al., 2001; Krass et al., 2013; Sohn, 2008). Hence, we propose Hypothesis 3.

Hypothesis 3. *RS* and *TS* can promote firms' technology level and innovation, and thereby improve *CEP*.

2.2.3. CEM III: Supply chain

Supply chain management plays a crucial role in environmental management by reducing the emission intensity of production through sourcing materials from low-carbon suppliers (Zhou, 2023). With trade liberalization and rapid development of *ICT*, information sharing in trade networks increases the similarity of firms' product mix, thereby enhancing market rivalry. However, it also benefits firms by providing more information about factor supply and market demand. Firms can more easily find suppliers of intermediate inputs and thus implement supply chain strategies. Moreover, since imported intermediate inputs usually contain more advanced cleaner production technologies (Ethier, 1982; Markusen, 1989), rivalry pressure forces firms to broaden the range of suppliers of intermediate imports to improve product quality. Thus, Market Rivalry Signal motivates firms to broaden intermediate imports for cleaner production. We propose Hypothesis 4.

Hypothesis 4. *RS* compels firms to enhance their corporate supply chain management by diversifying input sources and expanding product varieties, thereby leading to an improvement in *CEP*.

3. Method and data

3.1. Measurement of Rivalry Signal and Technology Spillover

Referring to product space theory (Hidalgo et al., 2007; Bloom et al.j, 2013; Hoberg & Philips, 2016), we construct the indicators representing *MS* and *TS* based on firms' information exchange with their market rivals in export networks by the China Customs Database for the period 2000 to 2016.

The product space theory, developed by Hidalgo et al. (2007), states that various products inherently contain production-related information with varying degrees of similarity in terms of inputs, technology, and management, determining the extent of knowledge transfer and spillovers. Consequently, we utilize this theory to quantify knowledge spillovers from competitors, denoted as Technology Spillover (*TS*). Export network-based information exchange serves as a critical conduit for such spillovers among firms, as highlighted by Yu et al. (2023). Notably, this exchange facilitates the dissemination of knowledge through product space networks, allowing firms to gain insights into non-produced products.

Inherent production information in products simultaneously exacerbates rivalries among enterprises. Referring to Bloom et al. (2013) and Hoberg and Philips (2016), we construct the indicator of Market Rivalry Signal (*RS*) that captures the similarity in production structures between firms and their industry competitors, based on information exchange within the export network. The rationale behind this indicator is that increased information sharing within the export network enhances consensus in decision-making, resulting in a more uniform production structure and, consequently, heightened market rivalry. The detailed construction of the indicators, *RS* and *TS*, is outlined in the subsequent section.

3.1.1. Indicator construction

(1) Rivalry Signal (*RS*)

The specific construction of the indicator *RS* is outlined below.

Firstly, we calculate the share of the firm i's exports of an HS4 code product k to firm i's exports of industry j to which the *HS4* code product belongs in year t (s^{i}_{jkt}). Similarly, we calculate all the other firms' (firms other than firm i, denoted as o) share of the HS4 code product k to all the other firms' (firms other than firm i, denoted as o) exports of industry j to which the *HS4* code product belongs in year t (s^{o}_{jkt}).

These two proportions s^{i}_{jkt} and s^{o}_{jkt} both represent the export proportion of product k in industry j. When the firm i's export share of product k (s^{i}_{jkt}) is close to all the other firms' export share of product k (s^{o}_{jkt}), firm i's product structure is more similar to the other firms concerning product k. Therefore, firm i experiences increased market rivalry for product k.

Referring to Bloom et al. (2013), we sum the product of s^{i}_{jkt} and s^{o}_{jkt} of any commodity k produced by firm i in industry j to obtain the index φ^{io}_{jt} representing market rivalry among firm i and other firms o in industry j. Equation (1) shows the detailed construction of the indicator, where φ^{io}_{jt} takes value in the range [0,1]; the closer this value is to 1, the greater the degree of market rivalry between firm i and other firms o in industry j.

$$\varphi^{io}_{jt} = \frac{\sum_{k\in j} s^{i}_{jkt} s^{o}_{jkt}}{\sqrt{\left(\sum_{k\in j} s^{i}_{jkt} s^{i}_{jkt}\right)\left(\sum_{k\in j} s^{o}_{jkt} s^{o}_{jkt}\right)}}. \tag{1}$$

Secondly, the enhanced market rivalry of industry ($\varphi^{io}_{jt}\overline{N}_{jt}$) shown in Equation (2) can be obtained by multiplying the market rivalry of industry j (φ^{io}_{jt}) by the standardized number of firms in industry j in year t ($\overline{N}_{jt}$), which stands for the strengthening effect of industry rivalry.

Finally, since a firm occupies a large product share in an industry with a high degree of market rivalry can enhance industry competition, we take the share of firm i's export in industry j to firm i's total export in year t as the weight of the enhanced market rivalry of industry ($\varphi^{io}_{jt}\overline{N}_{jt}$). As shown in Equation (2), we obtain the overall market rivalry (RS_{it}) faced by firm i in the market, including all industries. The larger RS_{it}, the greater the degree of Market Rivalry (Signal) faced by firm i.

$$RS_{it} = \ln\left[\sum_{j\in I_j} s_{ijt}\varphi^{io}_{jt}\overline{N}_{jt}\right], \tag{2}$$

where, $\overline{N}_{jt} = \sum_{k\in j} N_{kt} / \sum_{k\in j} 1$.

(2) Technology Spillover (*TS*)

The construction of the indicator, *TS*, is detailed as follows:

Firstly, we calculate the similarity between any two industries on the basis of product space theory referring to Hidalgo et al. (2007) and Yu and Dong (2020). The specific calculation is shown in Equation (3):

$$\phi_{jj't} = \min\left\{\frac{N_{j\cap j',t}}{N_{jt}}, \frac{N_{j\cap j',t}}{N_{j't}}\right\}, \tag{3}$$

where N_{jt} is the number of firms export in industry j in year t and $N_{j\cap j',t}$ is the number of firms export both in industries j and j' in year t. Therefore, $N_{j\cap j',t}/N_{jt}$ represents the conditional probability of the firm export in both industry j and j' given the firm exports in industry j in year t. The implication of $N_{j\cap j',t}/N_{j't}$ can be analyzed by analogy. The minimum value of $N_{j\cap j',t}/N_{jt}$ and $N_{j\cap j',t}/N_{j't}$ is used to measure the similarities between industries ($\phi_{jj't}$), which specifically represents the similarity of production technology between industries j and j' with value range [0,1]. The larger the value, the more similar technology are used in production between the two industries, and thus have greater Knowledge Spillovers.

Secondly, multiplying industry similarity ($\phi_{jj't}$) with the number of common firms in both industries j and j' ($N_{j\cap j',t}$), where $N_{j\cap j',t}$ can be interpreted as the scale effect of Knowledge Spillovers. The average knowledge spillovers in industry j from other industries j' are calculated by summing across all industries and dividing by the total number of industries (n), as shown in the parentheses in Equation (4).

Finally, taking the proportion of firm i's export volume in industry j as the weight(s_{ijt}),the weighted sum of Knowledge Spillovers received by industry j from other industries j' is the overall Knowledge Spillover received by firm i from the export network (TS_{it}), as shown in Equation (4), which we also use as the proxy for Technology Spillover.

$$TS_{it} = \ln\left[\sum\nolimits_{j\in i_j} s_{ijt} \cdot \left(\frac{1}{n}\sum\nolimits_{j'} \phi_{jj't} N_{j\cap j',t}\right)\right] \quad (4)$$

3.1.2. Characteristics of *RS* and *TS*

This study uses the China Customs database to calculate the *RS* and *TS*. The database records the customs clearance trade of all Chinese exporters and importers since 2000 to 2016, including information on product prices, quantities, and export destinations.[3]

The correlation between *RS* and *TS*[4] is far less than 1, indicating that the two indicators are relatively independent. Table 1 lists the values of *RS* and *TS*, which widely vary across different manufacturing industries. *RS* is highest in the "Manufacture of furniture" industry, on the contrary, *RS* is lowest in the "Processing of petroleum, coal and other fuel" industry. In addition, *TS* is highest in the "Manufacture of plastic products", followed by "Manufacture of computers, communication and other electronic equipment", "Manufacture of general (special) purpose machinery" and "Manufacture of electricity machinery and apparatus" industries with high technology. *TS* is generally lower in low-tech industries, such as "Processing of food from agriculture products" or "Manufacture of foods". These results are consistent with the existing studies (Liu & Yang, 2019), which support the rationality of the index construction in this study.

Fig. 2 presents a scatter plot depicting the temporal relationship between Rivalry Signal (*RS*) and Technology Spillover (*TS*). Each point on the plot represents an enterprise, with the x-coordinate signifying the enterprise's *RS* value and the y-coordinate representing its *TS* value for a given year. The plot reveals two key observations over time: Firstly, the increasing number and density of points reflect the rise in Chinese export firms,[5] suggesting a greater possibility for the increasement of enterprise rivalry and technology spillover. Secondly, the scatter points' general movement towards the upper right indicates a synchronous annual increase in both *RS* and *TS*.

Notably, the lack of a discernible functional relationship among the scatter points underscores the independence between *RS* and *TS*, further validating the effective separation of *RS* and *TS* in this paper.

3.2. Empirical model and the data description

We employ a two-way fixed effects model, as shown in Equation (5), to empirically test our hypotheses while controlling for time and firm fixed effects. The subscripts i, p, and t denote the firm, region and year, respectively; $\ln USE_{it}$ is the SO_2 emission intensity of firm i in year t; $MRS_{i,t-1}$ is the logarithm of Market Rivalry Signal faced by firm i in year t-1; $TES_{i,t-1}$ is the logarithm of Technology Spillover of firm i in year t-1; $X'_{i,t-1}$ includes the control variables at the firm level; Z'_{ipt} includes the control variable of province p where firm i operates in year t; λ_i is the firm fixed effect; μ_t represents the time fixed effect; and ε_{it} refers to the residual of the estimation equation.[6] Detailed descriptions of these indicators are provided below.

$$\ln USE_{it} = \beta_1 RS_{i,t-1} + \beta_2 TS_{i,t-1} + X'_{i,t-1}\gamma + Z'_{ipt}\delta + \lambda_i + \mu_t + \varepsilon_{it}. \quad (5)$$

(1) Explained variable: Firms' sulfur dioxide emission intensity (SO_2)

Considering the predominant use of coal as energy source in China, sulfur dioxide emissions from coal form the main pollutants emitted by firms. In line with existing studies utilizing Chinese data (Yu et al., 2022), this research adopts sulfur dioxide emission intensity (ln*USE*) as the indicator of *CEP*. This is determined by dividing the annual SO_2 emissions (in kilograms) by the real gross industrial output value (in thousands of yuan), deflated by the 2000 provincial producer price index to adjust for inflation. Notably, ln*USE* is an inverse proxy for *CEP*, with lower values signifying better *CEP* and higher values indicating the converse.

(2) Core explanatory variables (*RS* and *TS*)

Rivalry Signal (*RS*) and Technology Spillover (*TS*) are the key explanatory variables in this paper. Fig. 3 categorizes enterprises by their levels of *RS* and *TS* and plots their emission intensities. Across all indicators, firms at the 90th percentile consistently exhibit lower pollution emission intensities than those at the 10th percentile. Notably, there is a significant leftward shift in the pollution emission intensity of enterprises over time, particularly for those at the 10th percentile. This trend suggests that, against the backdrop of emission reduction efforts (Lee et al., 2024; Pan et al., 2024), enterprises are increasingly focusing on sustainable development and

[3] Highly limited data in specific industries may overestimate Technology Spillover and Market Rivalry. Thus, in actual measurement, this study eliminates the subdivided industry that contains products less than two and the subdivided industry that contains products less than 1% compared with similar subdivided industries. At the same time, considering that excessive elimination may lead to sample selection problems, this study only excludes products with less than 10, 15, and 20 export enterprises, with results that are still robust. Therefore, products with more than 1% export enterprises are uniformly used for empirical tests in this paper without losing generality.

[4] The correlation coefficient calculated based on the customs data sample is 0.3473, while the coefficients based on the combined sample (customs data and industrial enterprise pollution data) and regression sample are 0.3913 and 0.4029, respectively.

[5] The data integrity for the years 2015 and 2016 was compromised due to missing values.

[6] To reduce the endogeneity of the model, we lag all the firm-level variables in the regression by one stage.

Table 1
RS and *TS* in different industries.

Code	Industry	*RS*	*TS*	Code	Industry	*RS*	*TS*
13	Processing of food from agriculture products	5.35	3.03	28	Manufactures of chemical fibres	5.55	5.08
14	Manufacture of foods	5.26	2.55	29	Manufacture of rubber products	5.37	5.69
15	Manufacture of liquor, beverages and refined tea	4.51	2.9	30	Manufacture of plastic products	5.76	6.64
16	Manufacture of tobacco	5.48	5.97	31	Manufacture of non-metallic mineral products	4.84	5.49
17	Manufacture of textile	5.64	5.07	32	Smelting and pressing of ferrous metals	4.89	5.62
18	Manufacture of textile, wearing apparel and accessories	6.15	5.79	33	Smelting and pressing of non-ferrous metals	4.83	4.7
19	Manufacture of leather, fur, feather and related products	5.8	3.69	34	Manufacture of metal products	5.25	5.89
20	Processing of timber, manufacture of wood, bamboo, rattan	5.18	5.29	35	Manufacture of general purpose machinery	4.68	6.47
21	Manufacture of furniture	6.82	6.1	36	Manufacture of special purpose machinery	4.66	6.43
22	Manufacture of paper and paper products	5.57	6.23	37	Manufacture of automobiles	5.25	5.5
23	Printing and reproduction of recording media	5.75	5.74	39	Manufacture of electricity machinery and apparatus	5.22	6.43
24	Manufacture of articles for culture, education, arts and crafts, sports and entertainment activities	5.62	5.31	40	Manufacture of computers, communication and other electronic equipment	5.12	6.52
25	Processing of petroleum, coal and other fuel	3.87	2.53	41	Manufacture of measuring instruments and machinery	4.57	5.79
26	Manufacture of raw chemical materials and chemical products	4.36	4.63	42	Arts and crafts and other manufacturing	5.25	5.13
27	Manufacture of medicines	4.08	4.51				

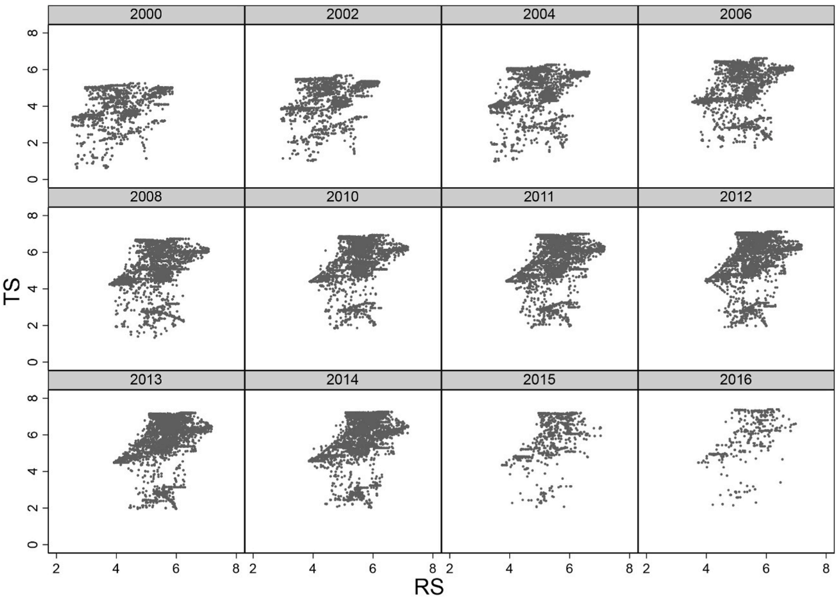

Fig. 2. The relationship between *RS* and *TS*.

emission reduction. Furthermore, *RS* and *TS* within export networks may be crucial factors in enhancing Corporate Environmental Performance (*CEP*).

(3) Control variables

This paper includes both firm-level and provincial-level control variables, referring to existing studies on micro-firm environmental performance (Jaraitė et al., 2022; Marin & Vona, 2021; Yu et al., 2022). Firm-level control variables include gross industrial output (ln*yt*), the logarithm of the firm's annual deflated industrial output. Export density (*r_EXP*) is expressed as a firm's annual exports divided by its total industrial output. Firm age (ln*age*) is the logarithm of the firm's age since establishment. The share of general trade (*r_ship*) is the proportion of a firm's annual general trade exports to its total exports; the share of trade exported to high-income

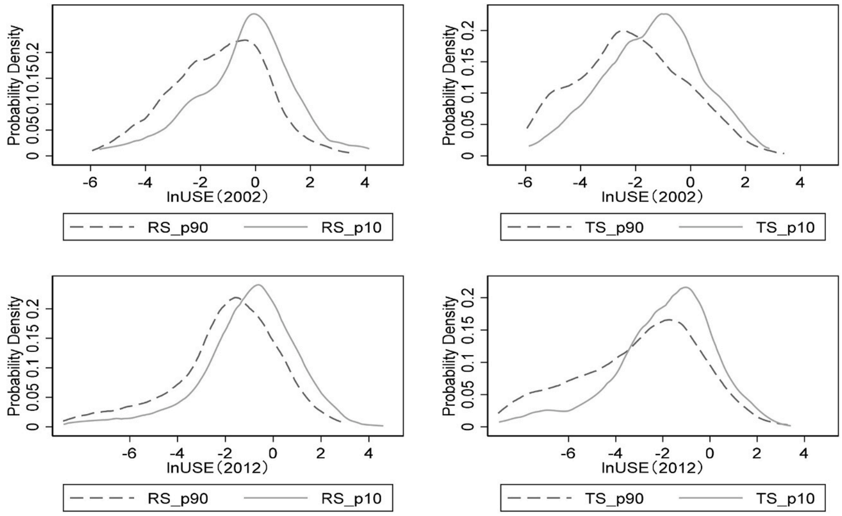

Fig. 3. Changes in pollution emission intensity of firms with high (low) *RS* and firms with high (low) *TS*.

countries (*r_HI*) is the amount of a firm's annual trade exported to high-income countries.[7]

In addition, provincial control variables reflecting the extent of foreign capital utilization, energy efficiency, population distribution and level of economic development have been added. These variables mainly include foreign investment utilization (*r_fdi*), measured by the ratio of the total foreign investment to provincial *GDP*; energy efficiency (ln*efficiency*), measured by the logarithmic value of the real industrial value added divided by the total energy consumption of the province; population density (ln*pop_d*), represented by the logarithmic of the population divided by the province's geographic area; and economic development level (ln*gdpper*), the logarithmic of the deflated nominal *GDP* per capita.

3.3. Data processing procedure and descriptive statistics

(1) China Customs Database

The export data of firms are from The China Customs database from 2000 to 2016. The *HS8* product code of export products is uniformly adjusted to the *HS6* product code of the 1996 version in this study. Given that import/export intermediaries do not directly produce products, their environmental performance is different from that of manufacturing firms, so these samples were excluded.

(2) Chinese Industrial Enterprise Pollution Emission Database

Pollution emission data at the enterprise level are obtained from the National Bureau of Statistics (*NBS*) database on the Chinese Industrial Enterprise Pollution Emission Database for the period 2000–2016. The database targets industrial enterprises whose pollutant emissions account for more than 85 per cent of the total pollutant emissions in each region.[8] These data are currently the most comprehensive environmental micro-data available in China. Most domestic studies on environmental performance and environmental performance of micro-firms are based on them (Chen & Chen, 2019).

(3) Other data sources

Exchange rate data are from the *World Bank* database; regional data such as *GDP*, population, geographical area and other macroeconomic information are mainly from the China Statistical Yearbook; *FDI* data are from the China Statistical Yearbook of Foreign Trade, and energy data are from the China Statistical Yearbook of Energy. The patent data employed in the discussion of Corporate Environmental Management (*CEM*) in Section 5 of this paper originates from the corporate patent database of the China National Intellectual Property Administration.

Table 2 reports the descriptive statistics of relevant variables. The mean value of SO_2 emission intensity of export firms (ln*USE*) is −1.854, the maximum value is 7.573, and the minimum value is −11.371. The maximum and minimum values show a considerable difference in SO_2 emission intensity within Chinese export firms.

[7] High-income countries are classified with reference to the United Nations Standard Classification of Countries. https://datahelpdesk.worldbank.org/knowledgebase/articles/378834-how-does-the-world-bank-classify-countries.

[8] To eliminate the effect of extreme values, the samples are winsorised at 1% and 99%.

Table 2
Descriptive statistics.

variable	N	mean	standard deviation	min	max
ln*USE*	98,479	−1.854	2.303	−11.371	7.573
RS	98,479	5.197	1.316	0.619	7.391
TS	98,479	5.127	0.850	2.516	7.179
lnyt	98,479	11.340	1.731	1.371	19.107
r_EXP	97,420	0.289	0.329	0.000	1.000
ln*age*	98,320	2.580	0.714	0.000	5.308
r_ship	98,479	0.779	0.366	0.000	1.000
r_HI	98,479	0.654	0.379	0.000	1.000
r_fdi	97,827	0.512	0.300	0.047	1.000
ln*efficiency*	97,827	5.474	0.890	0.000	7.673
ln*pop_d*	97,827	6.161	0.729	1.967	8.256
ln*gdpper*	97,827	10.116	0.577	7.923	11.334

The mean value of *RS* is 5.197, the maximum value is 7.391, and the minimum value is 0.619, reflecting considerable variation. Concerning *TS*, the mean value is 5.127, the maximum value is 7.179, and the minimum value is 2.516, which also shows an evident variation of *TS* within Chinese export firms. Notably, the rapid expansion of China's export market from 2000 to 2016 intensified the market rivalry, leading to tougher market competition for most firms.

4. Empirical results

4.1. Basic results

This study conducts a regression analysis based on Equation (5) to investigate the effect of *RS* and *TS* on *CEP*. Table 3 shows the regression results. Columns (1) and (2) examine the effects of *RS* on firms' SO_2 emission intensity; Columns (3) and (4) investigate the effect of *TS* on firms' SO_2 emission intensity, and Columns (5) and (6) simultaneously investigate the effects of *TS* and *RS* on firms' SO_2 emission intensity. In particular, Columns (1), (3), and (5) are results without control variables; Columns (2), (4), and (6) are results with other control variables.

Based on Columns (1) to (4), the separate effects of *RS* and *TS* on *CEP* indicate a significant reduction in firms' emission intensity at the 1% level. However, when investigated simultaneously in Columns (5) and (6), their inhibitory effects on emission intensity significantly decrease. Therefore, both the *RS* and *TS* contribute to improving *CEP*.

Table 3
Benchmark results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ln*USE*		ln*USE*		ln*USE*	
L.RS	−0.1171***	−0.0932***			−0.0932***	−0.0723**
	(0.0271)	(0.0281)			(0.0296)	(0.0305)
L.TS			−0.0776***	−0.0654***	−0.0492**	−0.0451**
			(0.0184)	(0.0187)	(0.0201)	(0.0203)
*L.*lnyt		−0.1200***		−0.1221***		−0.1192***
		(0.0103)		(0.0104)		(0.0104)
L.r_EXP		0.0507*		0.0432		0.0522*
		(0.0304)		(0.0301)		(0.0306)
*L.*ln*age*		0.0780**		0.0803**		0.0739**
		(0.0372)		(0.0367)		(0.0373)
L.r_ship		0.0365		0.0293		0.0281
		(0.0408)		(0.0409)		(0.0413)
L.r_HI		0.0282		0.0219		0.0263
		(0.0272)		(0.0272)		(0.0274)
r_fdi		−0.1110		−0.1248		−0.1068
		(0.1317)		(0.1311)		(0.1326)
ln*efficiency*		0.0622		0.0491		0.0609
		(0.0612)		(0.0608)		(0.0643)
ln*pop_d*		−1.3499**		−1.3578**		−1.3289**
		(0.6560)		(0.6433)		(0.6615)
ln*gdpper*		−0.7422**		−0.7513**		−0.7689**
		(0.3357)		(0.3283)		(0.3382)
R2	0.7976	0.8083	0.7978	0.8086	0.7980	0.8087
N	87445	78213	88493	79145	86381	77247

Note:(1) ***, ** and * are significant at 1%, 5% and 10% levels respectively; (2) In parentheses are robust standard errors of clustering to the firm level; (3) All regressions controlled for time fixed effect and firm fixed effect (the same below).

These results confirm Hypothesis 1, which posits that rival signals can enhance Corporate Environmental Performance (*CEP*) via two principal pathways: Market Rivalry Signal (*RS*) and Technology Spillover (*TS*). *RS* reduces information asymmetries among firms, escalating competition as competitors acquire advanced production techniques and market insights (Markou et al., 2023; Skilton & Bernardes, 2015). This increased rivalry prompts firms to enhance their supply chain management by sourcing higher-quality intermediate goods to manufacture cleaner products and may also induce a technological improvement effect. Conversely, *TS* upgrades firm technology and promotes green innovation, consequently improving *CEP*. Additionally, *TS* can also facilitate enterprises' switch to eco-friendly products (Barrows & Ollivier, 2018; Dong & Yu, 2021).

In terms of control variables, the total industrial output value (ln*yt*) is significantly negative, indicating that larger firms tend to have lower emission intensity. This can be attributed to the economies of scale and scope that large firms enjoy, which enable them to invest more in green production (Barrows & Ollivier, 2018).

Firm age (ln*age*) has a significantly positive effect on firms' emission intensity, indicating that the longer a firm has been in business, the greater its emission intensity. Older firms with more export experience are more likely to engage in production diversification, thereby increasing the likelihood of entering polluting industries (Dong & Yu, 2021).

Regarding regional control variables, the coefficients of population density (ln*pop_d*) and economic development level (ln*gdpper*) are significantly negative, this reflects that more densely populated or developed regions have lower emission intensities due to their higher environmental protection requirements.

In conclusion, *RS* and *TS* constitute distinct aspects of rivalry signals, and the benchmark results demonstrate that they collectively enhance *CEP*. Thus, omitting the pivotal variable of *RS* tends to overstate the impact of Technology Spillovers, a common pitfall in conventional trade-environment studies. The baseline results confirm Hypothesis 1 and imply that studies on the Pollution Halo Hypothesis may have overestimated the positive influence of technology spillovers by overlooking the Market Rivalry Effect.

4.2. Robustness test

(1) Discussion of endogeneity

We lag all firm variables by one period in the basic empirical regressions to mitigate possible endogeneity problems. However, there may be reverse causality between firms' product mix (used to construct *RS* and *TS*) and emission intensity. Firms may adjust their product mix in response to environmental regulations or consumers' environmental demands (Kang et al., 2018), leading to endogeneity in firms' product mix, the weight used to construct *RS* and *TS*. Following Bastos et al. (2018), we recalculate *RS* and *TS* using each firm's product share in the initial export year as weights and subsequently conduct benchmark regressions based on these revised values. The regression results in Table 4 show that *RS* and *TS* significantly reduce ln*USE* at the 1% significance level. Moreover, both the weak IV test and identification test support the validity of our instrumental variables, indicating that the regression results are less affected by the endogeneity problem, reconfirming the stability of the baseline results while supporting Hypothesis 1.

(2) The change of sample period and product codes

Given the significant data scarcity post-2014 as illustrated in Fig. 2, we have adjusted our analysis period to span from the year 2000–2014 for our regression analysis. The corresponding results in Columns (1) to (3) of Table 5, align with the outcomes of the benchmark regression.

To mitigate potential biases stemming from samples with disparate product classifications, we follow Bloom et al. (2013) by recalculating *RS* and *TS* using *HS3* and *HS6* codes, subdivided by *HS3* codes, respectively, and then regress. Corresponding results in Columns (4) to (6) of Table 5 show that the sign and significance of the coefficients for *RS* and *TS* are consistent with those in Table 3. This consistency further validates the reliability of our benchmark regression findings.

(3) Treatment of the omitted variable problem

We control for key policies that may influence *CEP* by including dummy variables for the "Pilot SO_2 Emissions Trading Policy (*PSP*) " and the "1000 Enterprises Energy Saving Actions" policy (*ESA*) in our baseline regression analysis, as shown in Columns (1) and (2), and Columns (3) and (4) of Table 6, respectively.

For the pilot SO_2 emissions trading policy (*PSP*), China's Ministry of Environmental Protection began piloting SO_2 emission reimbursement and trading policies, in 2002, in four provinces—Shandong, Shanxi, Jiangsu, and Henan—and three cities—Shanghai, Tianjin, and Liuzhou (including Huaneng Group), known as the "4+3+1″ project. In 2007, these pilots expanded to include Jiangsu, Tianjin, Zhejiang, Hebei, Shanxi, Chongqing, Hubei, Shaanxi, Inner Mongolia, Hunan, and Henan provinces. Consequently, we constructe a DID term for province and time: the province dummy is set to 1 if the enterprise is located in a national SO_2 emissions trading pilot province, and 0 otherwise; the time dummy is set to 1 after years 2002 or 2007, and 0 otherwise.

Regarding the "1000 Enterprises Energy Saving Actions" policy (ESA), the government oversees energy conservation in nine major energy-intensive sectors: iron and steel, non-ferrous metals, coal, electric power, petroleum and petrochemicals, chemicals, building materials, textiles, and paper-making. For this policy, we constructe a DID term for industry and time: the industry dummy is set to 1 if the enterprise's main industry is among the aforementioned nine energy-intensive sectors, and 0 otherwise; the time dummy is set to 1 for years 2006 and beyond, and 0 otherwise.

We also incorporate high-dimensional fixed effects for province × year in our analysis to address potential omitted variables. The

Table 4
Robustness test: IV Based on Initial Export Year.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ln*USE*		ln*USE*		ln*USE*	
L.RS	−0.3460***	−0.3006***			−0.2753***	−0.2543***
	(0.0565)	(0.0589)			(0.0523)	(0.0536)
L.TS			−0.2829***	−0.2289***	−0.1914***	−0.1563***
			(0.0560)	(0.0609)	(0.0507)	(0.0541)
Controls	No	Yes	No	Yes	No	Yes
N	80585	72132	82170	73563	79561	71198
LM stat.	1600.6666	1453.2064	779.4385	666.1784	842.4399	725.4435
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Wald stat.	1205.2298	984.5098	752.0696	611.5717	503.0823	408.2453

Note:(1)LM statistic for under identification test; (2)P-value is related to identification test; (3)Wald statistic for weak instruments.

Table 5
Robustness test: Changing Sample Period and Product Codes.

Varibles	(1)	(2)	(3)	(4)	(5)	(6)
	Year: 2000–2014			HS3 codes		
L.RS	−0.1086***		−0.0854***	−0.0746***		−0.0590**
	(0.0279)		(0.0303)	(0.0272)		(0.0297)
L.TS		−0.0742***	−0.0503**		−0.0516***	−0.0363*
		(0.0187)	(0.0203)		(0.0189)	(0.0201)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.8175	0.8177	0.8179	0.8097	0.8100	0.8109
N	76792	77708	75843	79093	79431	77729

Tabel 6
Robustness testing: treatment of omitted variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	PSP		ESA		High-dimensional FE	
L.RS	−0.0933***	−0.0723**	−0.0920***	−0.0709**	−0.0875***	−0.0650**
	(0.0296)	(0.0305)	(0.0296)	(0.0305)	(0.0288)	(0.0299)
L.TS	−0.0492**	−0.0452**	−0.0499**	−0.0457**	−0.0456**	−0.0416**
	(0.0201)	(0.0203)	(0.0201)	(0.0203)	(0.0198)	(0.0201)
PSP	0.0095	−0.0066				
	(0.0348)	(0.0389)				
ESA			0.0965***	0.0941***		
			(0.0283)	(0.0297)		
Controls	No	Yes	No	Yes	No	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year fixed effect	No	No	No	No	Yes	Yes
R2	0.7980	0.8087	0.7981	0.8088	0.8042	0.8148
N	86381	77247	86381	77247	86378	77242

Tabel 7
Heterogeneity analysis: Large Firms vs. Small Firms.

Variables	(1)	(2)	(3)	(4)
	Large firms		Small firms	
L.RS	−0.1370***	−0.1336***	0.0368	0.0450
	(0.0431)	(0.0425)	(0.0420)	(0.0420)
L.TS	−0.0610**	−0.0561**	−0.0618**	−0.0603**
	(0.0273)	(0.0270)	(0.0303)	(0.0304)
Controls	No	Yes	No	Yes
R2	0.8219	0.8232	0.7893	0.7903
N	36100	35965	36563	36117

results are presented in Columns (5) and (6) in Table 6.The regression findings from Columns (1) to (6) in Table 6 robustly validate our baseline findings, consistently showing that both Rivalry Signal (*RS*) and Technology Spillover (*TS*) significantly decrease SO_2 emission intensity (ln*USE*).

4.3. Heterogeneity analysis

The baseline results reveal the effects of *RS* and *TS* on *CEP*; however, these effects may vary with different characteristics of firms and regions. Therefore, this section examines the heterogeneous effects based on different characteristics of firms and regions.

(1) Large firms vs. Small firms

Empirical studies (Yang et al., 2020) show significant differences in production, sales, technology imitation and innovation between firms of different sizes. These differences affect the utilization of information and hence Corporate Environmental Performance. Based on firms' gross industrial output value (ln*yt*) in year *t-1*, we classify the sample into large-scale and small-scale firms using the median level as a threshold. We then examine the heterogeneous effects of *TS* and *RS* on *CEP* under different groups, with results presented in Table 7.

The empirical results suggest that *RS* significantly reduces large firms' emission intensity while having no significant effect on small firms. On the other hand, *TS* significantly reduces the emission intensity of both large and small firms, with a greater impact on the latter. This is because Technology Spillovers provide valuable production and management information that helps firms improve *CEP*. However, with the same level of technology spillovers, large firms may already have this information due to their capital, technology, and talent advantages compared to small firms. Moreover, small firms can take full advantage of technology spillovers through high imitation capabilities and innovation efficiency resulting from flexible organizational structures (Bound et al., 1984). Therefore, *TS* is particularly beneficial for small firms. As for Market Rivalry Signal, large enterprises, bolstered by advanced green technologies and lower production costs, are well-equipped to enhance *CEP* amidst competitive pressures. Conversely, small businesses, grappling with survival, find themselves ill-equipped to address the competitive drive for *CEP* improvements.

Moreover, Columns (1) and (2) show that *RS* exerts a greater influence than *TS* in big firms, suggesting that external competitive pressure is more effective in reducing emissions for firms than active learning through Technology Spillovers.

(2) Coastal cities vs. Inland cities

Coastal regions in China exhibit higher levels of openness and economic development due to their geographical location and early access to international markets. As a result, firms in coastal and inland regions behave differently regarding production, exports, and pollution emissions. We divide the sample into coastal and non-coastal firms to test this heterogeneity. Table 8 shows the empirical results indicating *RS* and *TS* significantly reduce the firms' emission intensity in the coastal provinces but not in the inland areas. Three possible reasons account for this.

Firstly, many pollution-intensive firms are clustered in coastal areas due to the facilitation of raw materials, technology, and trade. Therefore, the impacts of *RS* and *TS* on the firms' emission intensity in coastal areas are greater. Second, geographical advantages, better transportation infrastructure, and higher market openness enable coastal firms to access market information and international frontier technologies faster than firms in inland areas. Consequently, coastal firms can fully exploit Knowledge Spillovers in export networks to improve *CEP*. Third, due to the higher environmental protection awareness in coastal areas, local firms are more likely to improve *CEP* under the pressure of the local government and the public.

(3) Dual-control vs. Non-dual-control Areas

Due to China's coal-based energy structure, acid rain caused by SO_2 emissions used to plague industrial production and people's lives. In 1998, the Chinese government promulgated the "Acid Rain Control Zone and SO_2 Pollution Control Zone Plan" (starting now referred to as the "pollution control zone" policy), which divided 175 cities in 27 provinces into acid rain control zones or SO_2 pollution control zones.

We group firms into "pollution control zones" and "non-pollution control zones" according to firms' location and explore the heterogeneous effects of *RS* and *TS* on *CEP*. The empirical findings in Table 9 show that *RS* and *TS* significantly reduce the emission intensity of firms within the "pollution control zone" while having no impact outside this zone. The results imply that firms in the "pollution control zone" with higher emission intensities are more active in utilizing external information to improve *CEP* when faced with stricter environmental regulations.

5. The effects of rival singals on Corporate Environmental Management (*CEM*)

5.1. CEM I: Product switching

This section examines the impact of *RS* and *TS* on firms' product switch and *CEP*. We consider two product switching strategies for firms in China (Dong & Yu, 2021): switching to the firm's main product (the product with the largest proportion of the firm's export) and switching to the market core product (the product with the highest similarity with all others in the product space) as defined by

Table 8
Heterogeneous analysis: Coastal Cities vs. Inland Cities.

Variables	(1)	(2)	(3)	(4)
	Coastal cities		Inland cities	
L.RS	−0.0969***	−0.0815**	−0.0633	−0.0277
	(0.0334)	(0.0342)	(0.0629)	(0.0643)
L.TS	−0.0756***	−0.0664***	0.0090	0.0088
	(0.0241)	(0.0241)	(0.0355)	(0.0366)
Controls	No	Yes	No	Yes
R2	0.7960	0.8077	0.7915	0.8003
N	67237	60143	19138	17100

Table 9
Heterogeneous analysis: Dual-control vs. Non-dual-control Areas.

Variables	(1)	(2)	(3)	(4)
	Dual-control area		Non-dual-control area	
L.RS	−0.1197***	−0.0983***	0.0041	0.0297
	(0.0340)	(0.0350)	(0.0583)	(0.0596)
L.TS	−0.0518**	−0.0486**	−0.0264	−0.0248
	(0.0240)	(0.0244)	(0.0348)	(0.0346)
Controls	No	Yes	No	Yes
R2	0.8005	0.8110	0.7696	0.7814
N	69075	61794	17297	15447

Hidalgo et al. (2007). When firms switch to the market core product, they can more easily access advanced technology and management through external market information.

Considering the different types of information firms are exposed to under these two different reallocation modes, this study constructs two indicators to represent the tendency of product switching to the firms' main products (*Dist_IC*) and to the market core product (*Dist_MC*), as shown in Equations (6) and (7) respectively.

$$Dist\_IC_{it} = \sum\nolimits_j s_{ijt} \times \left(1 - \phi_{IC,jt}\right), \tag{6}$$

$$Dist\_MC_{it} = \sum\nolimits_j s_{ijt} \times \left(1 - \phi_{MC,jt}\right). \tag{7}$$

Consistent with the construction of previous indicators in this paper, the subscripts *i*, *j* and *t* represent the firm, product and year, respectively; s_{ijt} is the proportion of product *j* exported by firm *i* in its total export in year *t*; $\phi_{IC,jt}$ is the similarity of the product *j* exported by firm *i* and its main product *IC*. Thus, $1-\phi_{IC,jt}$ measures the distance between product *j* exported by firm *i* and its mian product *IC*. The larger the *Dist_IC*, the less the firm tends to switch to its main product.

Similarly, $\phi_{MC,jt}$ is the similarity of the product *j* and the core product of market (*MC*), while $1-\phi_{MC,jt}$ measures the distance between the product *j* and core product of market. Likewise, the larger the *Dist_MC* is, the less the firm tends to switch to the market core product.

We employ the mediating effect model to prove Hypothesis 2. The specific model is as follows:

$$Dist\_IC_{it}(Dist\_MC_{it}) = \beta_1 TS_{it-1} + \beta_2 RS_{it-1} + X_{it}'\gamma + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it} \tag{8}$$

$$\ln USE_{it} = \beta_1 TS_{i,t-1} + \beta_2 RS_{i,t-1} + \beta_3 Dist\_IC_{i,t}\left(Dist\_MC_{i,t}\right) + X_{i,t-1}'\gamma + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it} \tag{9}$$

Equation (8) explores the effects of *RS* and *TS* on firms' product switching strategies (*Dist_IC* or *Dist_MC*). Equation (9) tests whether such strategies affect firms' pollution emission.

Table 10 reports the empirical results of the regressions with *Dist_IC* and *Dist_MC* as mediating variables. Column (1) examines the effect of *RS* and *TS* on *Dist_IC* (the propensity of switching to firms' main product). The coefficients of *RS* is significantly positive, indicating that *RS* reduces the propensity of switching to firms' main products. However, the insignificant coefficient on *Dist_IC* in Column (2) suggests that product switch to firms' main products has no significant effect on *CEP*.

Column (3) examines the impacts of *RS* and *TS* on firms' propensity to switch to the market core products. The coefficients of *TS* are significantly negative, indicating that *TS* promote firms' product switching to the market core products. The coefficient of *Dist_MC* on emission intensity in Column (4) is significantly positive, suggesting that the greater the similarity between a firm's product and the market core product, the better its environmental performance. The empirical results of adding both *Dist_IC* and *Dist_MC* as explanatory variables are shown in Column (5), which are consistent with Columns (1) to (4).

In conclusion, *TS* encourages firms to align their product strategies with the market core product, which enables them to make the best use of market information, acquire cutting-edge technology and management expertise, and ultimately increase *CEP*. The above

Table 10
CEM I: Product switching.

Variables	(1)	(2)	(3)	(4)	(5)
	Dist_IC	ln*USE*	*Dist_MC*	ln*USE*	ln*USE*
Dist_IC		−0.0538			−0.0601
		(0.0847)			(0.0850)
Dist_MC				0.2732**	0.2756**
				(0.1127)	(0.1126)
L.RS	0.0118***	−0.0813**	−0.0019	−0.0856***	−0.0886***
	(0.0024)	(0.0329)	(0.0014)	(0.0328)	(0.0329)
L.TS	0.0021	−0.0462**	−0.0029***	−0.0449**	−0.0454**
	(0.0018)	(0.0222)	(0.0010)	(0.0220)	(0.0222)
Controls	Yes	Yes	Yes	Yes	Yes
R2	0.9642	0.8088	0.7736	0.8094	0.8094
N	70643	70643	70697	70697	69956

empirical results support Hypothesis 2.

5.2. CEM II: Technology and innovation

The mediating effect model shown in Equations (10) and (11) aims to explore the effect of *TS* on *CEM* (concerning technology and innovation) and *CEP*. We employ the number of patents as proxy variables to measure the technology level of firms according to conventional practice.

$$\ln Pat_{it} = \beta_1 RS_{it-1} + \beta_2 TS_{it-1} + X_{it}'\gamma + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it}, \tag{10}$$

$$\ln USE_{it} = \beta_1 TS_{i,t-1} + \beta_2 RS_{i,t-1} + \beta_3 \ln Pat_{i,t} + X_{i,t-1}'\gamma + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it}, \tag{11}$$

Equation (10) examines the impact of *TS* on firms' patent applications, where the dependent variable $\ln Pat_{it}$ is the logarithm of the total patents applied by firm *i* in *t*.[9] Equation (11) is used to investigate whether the increase in patent applications can reduce firms' emission intensity.

Taking into account the diverse technical requirements inherent in different patent application types, the standards for invention and utility model patents are notably more rigorous compared to those for design patents (Li & Zheng, 2016). Consequently, we categorize the patents into these three distinct types and conduct regression analyses for each. Columns (1) and (2), (3) and (4), (5) and (6), and (7) and (8) of Table 11 report the empirical results with the total number of firms' patents (ln*Pat*), total number of design patents (ln*Des*), total number of invention patents (ln*Inv*), and total number of [10] utility model patents (ln*Uti*) as the mediator variables, respectively.

The coefficients of technological spillover (*TS*) and Rivalry Signal (*RS*) on a firm's aggregate patent count, as well as on invention and utility model patents, are significantly positive, as indicated in Columns (1), (5), and (7). Moreover, the significant negative coefficients of patent-related indicators on firms' emission intensity, evident in Columns (2), (6), and (8), underscore the positive impact of *TS* and *RS* on *CEP* through technological upgrading. These findings further suggest that the promotion of *TS* and *RS* on innovation and its consequent positive effect on *CEP* are predominantly attributable to invention and utility model patents, rather than design patents. This divergence is likely due to the fact that technology spillovers primarily influence patents that contain substantial technical improvements. In summary, these empirical results confirm Hypothesis 3.

5.3. CEM III: Supply chain management

To prove Hypothesis 4, we use the indicator "variaty of imported intermediate inputs" and "country range of imported intermediate inputs" to represent the scope of intermediate goods inputs. Taking "variaty of imported intermediate goods" as an example, the specific mediating effect model is as follows:

$$\ln PN_{it} = \beta_1 TS_{it-1} + \beta_2 RS_{it-1} + X_{it}'\beta + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it} \tag{12}$$

$$\ln USE_{it} = \beta_1 TS_{i,t-1} + \beta_2 RS_{i,t-1} + \beta_3 \ln PN_{i,t} + X_{i,t-1}'\beta + Z_{ipt}'\delta + \lambda_i + \mu_t + \varepsilon_{it} \tag{13}$$

Equation (12) tests whether *RS* broadens the variaty of intermediate inputs imported by firms (ln*PN*), i.e. the variaties of intermediate inputs imported by firm *i* in the year *t-1* calculated based on *HS2* product code. Equation (13) tests whether the increase in ln*PN* reduces firms' pollution emission. Similarly, We can explore the mediating effect of the "country range of imported intermediate

[9] In the empirical regression, the number of patents is added with 1 and then treated as a logarithm, and the enterprises lacking patent data are treated by replacing it with 0.

[10] Considering that the HS4 product code is used to calculate *RS*, we also test its mediating effect, and the results show no significant difference.

Table 11
CEM II: Technology and innovation (patent).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln*Pat*	ln*USE*	ln*Des*	ln*USE*	ln*Inv*	ln*USE*	ln*Uti*	ln*USE*
ln*Pat*		−0.0324***						
		(0.0102)						
ln*Des*				−0.0151				
				(0.0174)				
ln*Inv*						−0.0670***		
						(0.0160)		
ln*Uti*								−0.0324**
								(0.0148)
L.RS	0.0650***	−0.0403	0.0126	−0.0367	0.0464***	−0.0432	0.0363**	−0.0414
	(0.0226)	(0.0422)	(0.0119)	(0.0420)	(0.0146)	(0.0422)	(0.0150)	(0.0424)
L.TS	0.0337**	−0.0383	0.0025	−0.0443	0.0192*	−0.0366	0.0332***	−0.0386
	(0.0153)	(0.0292)	(0.0071)	(0.0286)	(0.0108)	(0.0293)	(0.0111)	(0.0295)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.5477	0.8168	0.4775	0.8181	0.5342	0.8155	0.5093	0.8169
N	43190	43190	43240	43240	43274	43274	43207	43207

Table 12
CEM III: Supply Chain Management (Broadening intermediate inputs).

Variables	(1)	(2)	(3)	(4)
	*L.*ln*PN*	ln*USE*	*L.*ln*CN*	ln*USE*
*L.*ln*PN*		−0.0888***		
		(0.0148)		
*L.*ln*CN*				−0.0804***
				(0.0127)
L.RS	0.0572***	−0.1041***	0.0608***	−0.0996***
	(0.0156)	(0.0374)	(0.0188)	(0.0375)
L.TS	0.0074	−0.0421*	0.0068	−0.0435*
	(0.0109)	(0.0242)	(0.0132)	(0.0241)
Controls	Yes	Yes	Yes	Yes
R2	0.8262	0.7982	0.8464	0.7975
N	53770	53770	53799	53799

inputs" (ln*CN*), i.e. the number of countries of imported intermediate products by firms calculated by *HS2* product code.

In Table 12, the results of the intermediary variable (ln*PN*) are reported in Columns (1) and (2), and those of the variable (ln*CN*) are reported in Columns (3) and (4). The coefficients of *RS* on ln*PN* and ln*CN* in Columns (1) and (3) are significantly positive, indicating that *RS* broaden the scope of intermediate goods inputs of firms. The significantly negative coefficients of ln*PN* and ln*CN* verify the positive role of *RS* on *CEP* by supply chain management. Thus, Hypothesis 4 is supported.

6. Further discussion

This section will delve into the impacts of *RS* and *TS* from the exogenous perspective of the overall business environment in which the firm operates combined with the firm's product price and quality.

Tabel 13
The impacts of RS and TS under key industrial policies.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Central government		Local government		Central or local government	
L.RS	−0.0247	0.0012	−0.0228	0.0043	0.0117	0.0193
	(0.0334)	(0.0347)	(0.0366)	(0.0377)	(0.0365)	(0.0377)
L.TS	−0.0485**	−0.0437*	−0.0973***	−0.0849***	−0.1030***	−0.0789***
	(0.0222)	(0.0228)	(0.0280)	(0.0292)	(0.0269)	(0.0282)
KI L.RS*	−0.1110***	−0.0963***	−0.0912***	−0.0805***	−0.1262***	−0.0985***
	(0.0217)	(0.0229)	(0.0281)	(0.0292)	(0.0266)	(0.0285)
KI L.TS*	0.0816***	0.0698***	0.1023***	0.0856***	0.1257***	0.0903***
	(0.0220)	(0.0231)	(0.0287)	(0.0302)	(0.0270)	(0.0289)
Controls	No	Yes	No	Yes	No	Yes
R2	0.7976	0.8079	0.7974	0.8077	0.7980	0.8086
N	62447	55957	62447	55957	64737	57873

6.1. The impacts of RS and TS under key industrial policies

In China, the key industrial policies play an important role in directing economic development and facilitating structural adjustment (Dong et al., 2024; Yu et al., 2020). The key industrial policies aim to strategically employ supportive or restrictive measures to realize resource reallocation both within and between industries, thereby achieving the goal of supporting specific industries. Consequently, this study aims to further investigate the impact of *RS* and *TS* on *CEP* under the guidance of the key industrial policies.

Based on Equation (5), we incorporate the cross-multiplier terms of *RS* and *TS* with the key industrial policies, employing a moderating effect model to further investigate the moderating role of the key industrial policies (*KI*) in the impact of *RS* and *TS* on *CEP*. Drawing upon Yu et al. (2020) and Dong et al. (2024), this study extracts the keywords from official documents of the central government and provincial five-year plans spanning from the Ninth Five-Year Plan to the Twelfth Five-Year Plan, aiming to identify key industries that have received significant support from either the central government or local governments (provinces) in corresponding years. *KI* is set to 1 if it is the key industry supported by the government, and 0 otherwise.

Specifically, this paper incorporate the cross-multiplier of the key industries supported by the central government with *RS* and *TS*, the cross-multiplier of the key industries supported by the local governments with *RS* and *TS*, and the cross-multiplier the key industries supported by both of the central and local governments with *RS* and *TS* in Equation (5), respectively. The corresponding empirical results are shown in Table 13, in which the Columns (1) and (2), and Columns (3) and (4), and Columns (5) and (6) correspond to the results of the key industries supported by the central government (if the industry is a key industry supported by the central government, *KI* takes 1, otherwise 0), key industries supported by the local government (if the industry is a key industry supported by the local government, *KI* takes 1, otherwise 0), key industries supported by the central and local governments (if the industry is a key industry supported by the central or the local governments, *KI* takes 1, otherwise 0).

The regression results confirm the robustness of the benchmark findings. In addition, the coefficients of the cross-multiplier terms indicate that the key industrial policy combined with *RS* reducing firms' SO_2 emission intensity, and the key industrial policy combined with *TS* increasing firms' SO_2 emission intensity.

The primary reason for these results lies in the fact that, based on the previous findings of this study, an increase in firms' Rivalry Signal (*RS*) enhances corporate supply chain management. This is reflected by an expansion in both the variety and country range of imported intermediate goods. According to Yu et al. (2020) and Dong et al. (2024), the key industrial policy provides export firms with more favorable policies and incentives, thereby facilitating the optimization of their supply chains management to reduce emission intensity.

For the *TS*, key industrial policies belong to selective industrial policies, and existing literature suggests that such policies distort resource allocation, undermine market efficiency, and interfere with firms' business operations (Huang et al., 2021), including firms' product switching strategies as well as research and development (R&D) strategies – both of which serve as crucial channels through which *TS* impact *CEP*. Consequently, the key industrial policies hinder the influence of *TS* on firms' product switching strategies and R&D strategies, thereby dimishing the enhancement of *TS* on *CEP*.

6.2. The impact of RS and TS on the price and quality of firms' products

The previous analysis investigated the influence of *RS* and *TS* on *CEP*, as well as on *CEM*, encompassing firms' product selection, technology and innovation, and supply chain management. Moreover, this paper endeavors to examine the impact of *RS* and *TS* on firms' product quality and pricing.

In the measurement of product quality (ln*EQ*), referring to Feng et al. (2017), the demand equation and the export price and quantity information of firms' various types of products are used to regress and obtain the residuals, as demonstrated in Equation (14).

$$\ln Q_{ijt} = -\sigma \ln P_{ijt} + \alpha_{jt} + \mu_{ijt} \tag{14}$$

where α_{jt} denotes the fixed effect at the product-year level, μ_{ijt} represents the error term, and σ represents the elasticity of substitution of different products. The residuals can be used to calculate the average quality of the product and then averaged to the firm level. The unit price (ln*Price*) is the total export value divided by the export quantity.

The corresponding regression results are shown in Table 14, where Columns (1) and (2) and Columns (3) and (4) show the regression results of *RS* and *TS* on product quality and product unit price, respectively. The results show that *RS* elevate the price of the product without improving its quality, while *TS* enhances both the quality and price of the product simultaneously.

The possible reasons for these empirical findings are as follows: the enhancement of *CEP* necessitates supplementary inputs and appropriate financial remuneration, which in turn results in an escalation of prices. Additionally, *TS* improves both *CEP* and product quality simultaneously. Consequently, the observed price increase can be attributed to the compensation required for the enhancement of both *CEP* and product quality.

7. Conclusions and policy implications

This paper is the first to explore the role of *RS* and *TS* on *CEP* and how the rival signals affect *CEP* through *CEM*. We innovatively identifies the *RS* and *TS* from firms' information exchange with their market rivals in export networks, then explore their different effects on *CEM* and *CEP*. The study has the following key findings. Firstly, Market Rivalry and Technology Spillover, i.e., two opposing rival signals, simultaneously improve *CEP*. This result also suggests that the positive role of technology spillover was likely

Tabel 14
Impact of RS and TS on product quality and price.

Variables	(1)	(2)	(3)	(4)
	ln*EQ*		ln*Price*	
L.RS	0.0741	0.0641	0.4924***	0.5000***
	(0.0538)	(0.0576)	(0.0842)	(0.0920)
L.TS	0.1216***	0.1122**	0.3195***	0.2966***
	(0.0423)	(0.0453)	(0.0634)	(0.0677)
Controls	No	Yes	No	Yes
R2	0.6834	0.6902	0.7879	0.7945
N	71028	63532	71028	63532

overestimated in previous studies related to **Pollution Halo Hypothesis**. Secondly, the heterogeneity analysis shows that *RS* and *TS* matter primarily in large firms and more polluted areas, such as "coastal cities" and "dual control zones". Finally, the investigations of the impacts of rival signals on *CEM* show that *RS* could promote firms' innovation and firms' supply chain management. At the same time, *TS* could promote firms' innovation and firms' product switching toward the market core product. Consequently, the enhancement of *CEM* by rival signals improves C*EP*.

This study unveils the significant positive environmental impacts of firms' information sharing with their market rivals in the export network. Moreover, this study underscores the noteworthy role of *RS* on *CEP* and reveals the overestimated improving effects of *TS* on *CEP* due to the neglect of *RS* in previous literature.

Within the context of the green economy, sustainable development, and global climate change mitigation, this study offers insights for both corporate management practices and government policy implementation.

The managerial implications for firms are threefold. First, firms should leverage technology spillovers by promoting information exchange in market networks. Our research indicates that *TS* can boost *CEP* both quickly through product switch and over time through technological innovation. While product switching provides immediate benefits, long-term gains in *CEP* are dependent on a slow and steady process of technological advancement. Firms must balance short-term product switch with a commitment to long-term technological progress to ensure sustainable production.

Second, our study reveals that broadening the range of intermediate inputs and imports can enhance *CEP*. Consequently, firms can enhance sustainable green production through the optimization of supply chain management and the expansion of their international supply chains.

Third, firms should maintain a seamless flow of information channels and strengthen their information processing capabilities, particularly through digital transformation. It is crucial for firms to align green production with digital strategies effectively.

For the government, we propose the following policy recommendations: First, the government should uphold market principles and ensure fair competition. This study reveals that *TS* helps improve *CEP* in the short term through product switch. Therefore, the government should facilitate firms' product switch by lowering entry and exit barriers.

Second, the government should foster a transparent and open environment to enhance the clean effects of information exchange among competitors within market networks. Both *RS* and *TS* significantly improve *CEP*, with their effectiveness being highly dependent on the smooth flow of information. Efficient information exchange is crucial for firms to rapidly and effectively convert external information into actionable production insights.

Third, this paper reveals that *RS* and *TS* improve *CEP* by promoting firms' innovation. Thus, policies should focus on steering innovation towards clean technologies and encouraging firms to leverage technology spillovers for green production and innovation.

Submission declaration and verification

The manuscript has not been submitted anywhere in any other form.

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None.

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Declarations of interest

None.

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Data availability

The data that has been used is confidential.

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