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The Impact of Gradual Expectation Shocks from the EU CBAM on Exports and Carbon Emissions in China's High-Carbon Industries: A Multi-Period DID Model

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Abstract. The EU Carbon Border Adjustment Mechanism (CBAM) is marked by a gradual policy shock with poor expectations in 2018 and high expectations in 2021. The study is based on 2018-2022 and uses a multi period difference-in-differences (DID) model to examine the gradient impacts of gradual CBAM expectations on exports to Europe and carbon emissions in the five major high-carbon sectors in China and also tests the moderating effects of carbon intensity. The results indicate that the CBAM expectation shock exerts a significant gradient-dependent inhibitory effect on exports to Europe from high-carbon industries, as well as a significant gradient-dependent emission-reduction effect on carbon emissions. The effects during the strong expectation phase are significantly stronger than those during the weak expectation phase, and carbon intensity plays a significant positive moderating role. This study fills a research gap regarding policy expectation phases and provides empirical evidence for China's high-carbon industries to address carbon barriers and advance low-carbon transformation.

Keywords: CBAM, multi-period DID, high-carbon industries, carbon emissions

1. Introduction

Global climate regulatory bodies and international trade regulations are closely interconnected and cross border carbon pricing has become a fundamental regulation instrument to transform the trade landscape of high carbon industries. Being the first operational policy to introduce a cross-border carbon barrier in the world, the EU Carbon Border Adjustment Mechanism (CBAM) is not only one of the primary tools that the EU can use to reduce carbon leakage and set its carbon neutrality objectives but also a blueprint that other developed countries may follow to set up carbon trade barriers [1, 2]. The way it shapes the rules challenges the exports of high-carbon products of developing countries systematically. The initial version of the policy was proposed in 2018, and a legislative draft was released in 2021, and transitional rules in 2022. The transition phase started in 2023, and carbon pricing will start to be formally implemented in 2026. Instead of being a policy shock, the policy is designed to increase gradually, with low expectations in 2018 and high expectations in 2021 and focuses on five key high-carbon industries, which are steel, aluminum, cement, fertilizers, and electricity [3, 4].

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Being the biggest importer of high-carbon products to the EU, China is especially sensitive to the effects of the CBAM, and the question of its potential outcomes has become the center of interest of the studies in both the local and international academic communities [5-9]. The literature available upholds the truth that the CBAM raises the cost of exporting the high-carbon industries because of the internalization of carbon costs and leads to a reduction in export volumes and low levels of emission reduction effects [10]. However, these studies are badly constrained: they are primarily focused on the period of official policy execution, and they are not divided by sector, in addition, their identification strategies are less desirable in determining the gradient effects in case of gradual policy shock, they are not able to well determine the gradient effects at the stage of CBAM anticipation [11, 12].

In fact, during the 2018–2022 period—from the proposal of the CBAM policy concept to the finalization of the transitional rules—China's high-carbon industries had already formed phased policy expectations and adjusted their production and export strategies in stages. This quasi-natural experiment provides an ideal setting for employing the multi-period difference-in-differences (DID) method to identify the dynamic impact of the policy [9].

Based on this, this paper argues that the 2018–2022 period is an appropriate sample period. It designates China's five high-carbon industries directly covered by CBAM as the treatment group and five non-high-carbon industries as the control group, and constructs an empirical identification model centered on the multi-period difference-in-differences (DID) method. It further develops a systematic framework to identify the dual dynamic effects of CBAM's incremental expectation shocks on China's high-carbon industries' exports to Europe and carbon emissions, and establishes a testing pathway for the core moderating role of carbon intensity.

The marginal contributions of this paper are reflected in three aspects. First, in terms of research perspective, the study focuses on the 2018–2022 policy anticipation period, precisely designing models to capture the gradual impact characteristics of CBAM—from "weak expectations to strong expectations"—and establishing a framework for identifying the dynamic impact effects of policy anticipation, thereby addressing the gap in existing research regarding insufficient attention to the policy anticipation phase [13]. Second, regarding the research subjects, the model covers five major high-carbon sub-sectors, enabling a precise decomposition of sector-specific impact characteristics and providing micro-level evidence for formulating differentiated response strategies for various high-carbon industries [3, 8]. Third, regarding research methodology, this paper constructs a rigorous dynamic causal identification model framework using a multi-period difference-in-differences approach. The moderating role of carbon intensity is explicitly specified and empirically tested, providing a methodological reference for the empirical analysis of incremental impacts of cross-border carbon policies, as well as empirical evidence for developing countries in responding to carbon tariff policies [9, 14].

2. Institutional context and research hypotheses

2.1. Institutional context and policy characteristics of the CBAM

The introduction of the EU CBAM stems from the issue of carbon leakage following the implementation of the EU Emissions Trading System (EU ETS). It serves as a core policy for the EU to balance internal and external carbon costs and maintain the competitiveness of domestic industries, while imposing asymmetric trade constraints on developing countries [12, 15]. The evolution of this policy has formed a clear, gradual path of expectation transmission, thereby providing a practical foundation for applying the multi-period difference-in-differences method. In

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2018, the EU first proposed the concept of cross-border carbon adjustment in the "Long-Term Strategy for the Climate Action and Energy Union," clarifying the scope of regulation for high-carbon industries, which became the starting point for weak market expectations regarding the policy. In 2021, the EU published the "Draft Carbon Border Adjustment Mechanism," establishing core rules and solidifying the policy framework, which led to strong policy expectations in the market. In 2022, the EU finalized the transitional implementation rules, with the implementation of policy details further strengthening market incentives for adaptation [2, 11].

The core of CBAM is to internalize production-side carbon costs into international trade, combining both emission reduction and trade protection attributes. It imposes highly targeted constraints on China's high-carbon industries. First, the industry coverage aligns closely with China's high-carbon export products to the EU, resulting in a significant direct policy impacts [5, 7, 8]; second, the accounting methodology increases compliance costs and accounting complexity for Chinese exporters; third, the carbon price is pegged to the EU ETS price, and price volatility amplifies the uncertainty of export costs for China's high-carbon industries; fourth, the policy is implemented gradually, and the transition period does not provide sufficient time for high-carbon industries in developing countries to transition to low-carbon practices, creating an asymmetric impacts [4, 10].

2.2. Theoretical analysis and research hypotheses

Based on carbon leakage theory and cross-border carbon pricing theory, the incremental anticipatory impact of CBAM affects the export and carbon emission behavior of China's high-carbon industries in phases through multiple channels. The conceptual transmission framework is presented in Figure 1. Carbon intensity, as a core industry characteristic, plays a key moderating role in the magnitude of impact effects across different phases.

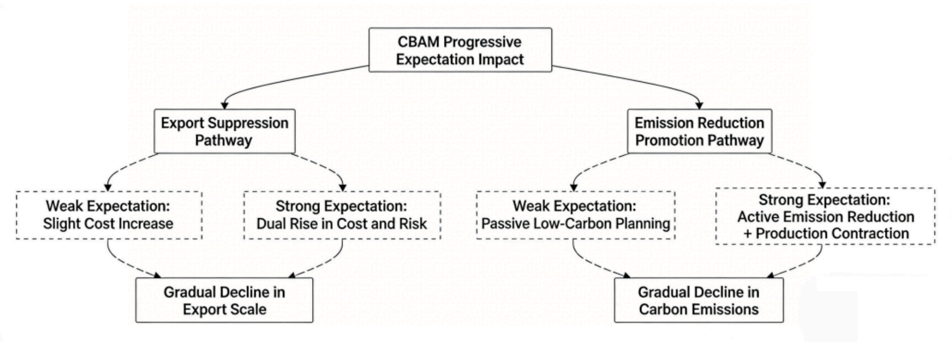

Figure 1. Conceptual framework for the transmission of export and emission reduction effects from gradual CBAM shocks

In terms of export behavior, the gradual anticipatory effect of CBAM has a graded inhibitory effect on exports through two channels: cost increases and risk aversion. In 2018, when expectations of carbon compliance costs were weak, enterprises only formed very vague expectations of carbon compliance costs and made limited investments in carbon emission monitoring and accounting. Therefore, the increase in export costs was small, and the overall inhibitory effect on exports to Europe was relatively weak. In the 2021 phase of strong expectations, the enforcement of core rules enabled enterprises to form clear expectations of carbon tariff costs and carbon compliance costs.

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The marginal cost of marginal exports increased significantly. In addition, enterprises faced trade risks resulting from rule adjustments, carbon price volatility, and the bandwagon effect of carbon barriers globally. Enterprises made significant adjustments to their export strategies and reduced their dependence on the EU, leading to a much stronger inhibitory effect on exports [9].

In terms of carbon emission behavior, the gradual impact of CBAM expectations generates a tiered reduction effect through both proactive emission reduction and passive contraction channels. During the 2018 phase of weak expectations, companies adopted conservative low-carbon transition plans, and their emission reduction efforts were largely reactive. In the strong expectation phase of 2021, clear expectations of carbon tariff costs compelled enterprises to increase investment in low-carbon R&D and optimize energy consumption structures. Simultaneously, the anticipated decline in export volumes drove enterprises to scale back production of high-carbon products. The synergistic effects of China's "dual carbon" policies and CBAM further strengthened enterprises' motivation to reduce emissions, leading to a significant enhancement of carbon reduction effects [7, 11].

Carbon intensity exerts a positive moderating effect on the gradual policy transmission of CBAM. In industries with higher carbon intensity, the proportion of carbon costs in total export costs is larger, and sensitivity to policy cost shocks is higher: during the weak expectation phase, the suppression of exports and carbon reduction effects in these industries was already significantly greater than in low-carbon-intensity industries; during the strong expectation phase, the scale of carbon tariffs that enterprises must pay increased substantially, further strengthening the motivation for export adjustments and proactive emissions reductions, and the policy shock effect became even more pronounced [3, 8].

Based on the above analysis, this paper proposes two core research hypotheses. H1: The gradual expectation shock of CBAM exerts a significant gradient-based suppression effect on the exports of China's high-carbon industries to Europe and on industry carbon emissions, and the effect during the strong expectation phase in 2021 is significantly stronger than that during the weak expectation phase in 2018. H2: Industry carbon intensity positively moderates the gradient effects of the CBAM expectation shock; the higher the carbon intensity, the more pronounced the impact during the weak expectation phase, and the greater the increase in the effect during the strong expectation phase.

3. Research design

3.1. Data sources and selection of samples

The time frame of this study is 2018-2022. Industry sampling was conducted based on the Classification of National Economic Activities (GB/T 4754-2017) to establish an industry-by-year balanced panel data that is the empirical foundation of estimating model parameters, finding effects, and testing them later. The treatment group includes five high-carbon industries being directly subject to the CBAM of the EU, including ferrous metal smelting and rolling, non-ferrous metal smelting and rolling, non-metallic mineral products, chemical raw materials and chemical products manufacturing, electricity and heat production and supply. There are five non-high-carbon industries in the control group that will not be affected by the CBAM, including food manufacturing, textiles, general machinery manufacturing, specialized machinery manufacturing, and automotive manufacturing. The two categories of industries are extremely close concerning the size of the industry, pattern of development, and availability of data, which meet the identification requirements of a multi-period difference-in-differences model [9].

The core sources of data required to estimate all the variables in the model have been identified in the paper as China Customs Database, China Emissions Accounting Database (CEADs), China

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Industrial Economic Statistical Yearbook, Wind industry Database, State Administration of Foreign Exchange and Eurostat. The data will be smoothed, truncated and the missing values will be imputed so that the data will be of good quality when applied on the model. These processing methods will fully adhere to the empirical research requirement to provide data support to the model estimation.

3.2. Variable definitions

In accordance with the research focus of this paper and the requirements of the multi-period difference-in-differences model, four categories of variables—dependent, core explanatory, moderating, and control variables—are designed for the empirical model. The measurement methods and data sources for each variable are detailed in Table 3-1.

Table 1. Variable definitions and data sources

Variable Type	Variable Name	Symbol	Measurement Method and Definition	Data Source
Dependent Variable	Exports to the EU	$Export_{it}$	Annual total exports to the EU by industry (in billions of yuan), deflated to 2018 base year	China Customs Database, State Administration of Foreign Exchange
Dependent Variable	Total Carbon Emissions	CO_{2it}	Annual fossil fuel consumption + carbon emissions from industrial production (10,000 tons of CO_2)	China Energy and Emissions Accounting Database (CEADs)
Dependent Variable	Carbon Intensity	$CO_2\_per_{it}$	Total carbon emissions / total industrial output value (tons of CO_2 per 10,000 yuan)	CEADs, China Industrial Economic Statistical Yearbook
Key Explanatory Variable	2018 Weak Policy Expectation Dummy Variable	$DID1_{it}$	1 if treatment group and t ≥ 2018, 0 otherwise	Constructed in this study
Key Explanatory Variable	2021 Strong Policy Expectation Dummy Variable	$DID2_{it}$	1 if treatment group and t ≥ 2021, 0 otherwise	Constructed in this study
Moderator	Baseline Carbon Intensity	$Cden_{base,i}$	2018 industry-specific carbon emissions per unit of output (tons of CO_2/10,000 yuan), industry-specific constant	CEADs, China Industrial Economy Statistical Yearbook
Control variable	Industry scale	$Scale_{it}$	Industry total industrial output value (10,000 yuan), deflated to 2018 base year	China Industrial Economy Statistical Yearbook, Wind
Control variable	R&D expenditure	$R\&D_{it}$	Industry R&D Expenditures (10,000 yuan)	China Industrial Economy Statistical Yearbook, Wind
Control variable	Foreign Investment Participation	FDI_{it}	Actual Utilized Foreign Direct Investment (10,000 yuan, deflated after RMB conversion)	Wind, State Administration of Foreign Exchange

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Table 1. (continued)

Control variable	Energy Consumption Structure Energyit	$Energy_{it}$	Share of Coal Consumption in Total Energy Consumption (%)	CEADs, China Industrial Economy Statistical Yearbook
Control variable	Export Dependency	Dep_{it}	Total Industry Exports / Total Industrial Output Value (%)	China Customs Database, China Industrial Economy Statistical Yearbook
Control variable	Industry Concentration	$CR4_{it}$	Output Value of Top 4 Enterprises as a Percentage of Total Industry Output Value (%)	Wind, Industry Statistical Reports

3.3. Model specification

This study employs the multi-period difference-in-differences method as the core identification technique, and successively constructs a baseline model, a moderating effects model, a parallel trends test model, and a dynamic effects model.

3.3.1. Baseline regression model

To examine the differentiated effects of the expected CBAM shock on exports and emissions reductions, a baseline model is constructed as equation (1):

$$Y_{it}=\alpha_0+\alpha_1 DID1_{it}+\alpha_2 DID2_{it}+\alpha_3 X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{1}$$

In this model, Y_{it} represents the dependent variable, which consists of the volume of exports to Europe ($Export_{it}$), total carbon emissions (CO2it), and carbon intensity ($CO2\_per_{it}$); $DID1_{it}$ and $DID2_{it}$ are the core explanatory variables; X_{it} is the vector of control variables, including industry size, R&D investment, and other control variables mentioned above; μ_i is the industry fixed effect, λ_t is the time fixed effect; ε_{it} is the random error term; α_0 is the intercept term, and α_1, α_2, and α_3 are the coefficients to be estimated.

3.3.2. Moderation effect model

To test the moderating role of carbon intensity, interaction terms are introduced into the baseline model as equation (2):

$$\begin{aligned}Y_{it}=&\beta_0+\beta_1 DID1_{it}+\beta_2 DID2_{it}+\beta_3 DID1_{it}\times Cden_{base,i}+\\&\beta_4 DID2_{it}\times Cden_{base,i}+\beta_5 Cden_{base,i}+\beta_6 X_{it}+\mu_i+\lambda_t+\varepsilon_{it}\end{aligned} \tag{2}$$

In this model, $Cden_{base,i}$represents the baseline carbon intensity; $DID1_{it}\times Cden_{base,i}$ and $DID2_{it}\times Cden_{base,i}$ are the core interaction terms used to identify the moderating effect of carbon

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intensity; β_0 is the intercept term; $\beta_1 \sim \beta_6$ are the coefficients to be estimated; and the definitions of the remaining variables are consistent with those in the baseline model.

3.3.3. Parallel trends test model

Parallel trends are a core prerequisite for the application of the difference-in-differences (DID) model, requiring that the dependent variables in the treatment and control groups exhibit consistent temporal trends prior to policy implementation. This study employs an event study approach to construct a parallel trends test model and verify this assumption as equation (3):

$$Y_{it}=\gamma_0+\sum_{k=-1}^{2}\gamma_k Event_{it}^{k}+\gamma_4 X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{3}$$

Here, $Event_{it}^{k}$ is a dummy variable representing the relative timing of the policy, with 2018 (the starting point of the weak-expectation policy) as the base period (k=0). K=-1 denotes 2017 (pre-policy period), k=-1 denotes 2019–2020 (post-weak-expectation phase), and k=2 denotes 2021–2022 (strong policy expectation phase); γ_k represents the coefficient to be estimated for the relative time dummy variable of the policy in each period, and the definitions of the remaining variables are consistent with those in the baseline model.

If γ_k is not significantly different from zero when k=- 1, this indicates that the treatment group and the control group satisfy the parallel trends assumption.

3.3.4. Dynamic effects test model

To clearly depict the annual dynamic changes in the expected impact of the CBAM from 2018 to 2022 and further verify the gradient-enhanced characteristics of the policy effects, this study decompose the policy timing by year and construct a dynamic effects model as equation (4):

$$Y_{it}=\delta_0+\sum_{t=2018}^{2022}\delta_t\cdot Year_{it}^{t}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{4}$$

In this model, $Year_{it}^{t}$ is an annual dummy variable that takes the value 1 if the industry is in the treatment group and the year is t, and 0 otherwise; δ_t is the coefficient to be estimated for the policy effect in each year, used to identify the intensity of the dynamic shocks associated with weak expectations in 2018, strong expectations in 2021, and other years. The definitions of the remaining variables are consistent with those in the baseline model.

The t-values reported in the table are the t-statistics for each regression coefficient, used to test the significance of the coefficients.

3.4. Robustness tests

To ensure the reliability of the estimation results, this paper designs robustness tests for the model from three key aspects.

First, cluster-adjusted standard errors. Standard errors are clustered at the industry level in all regressions to mitigate within-group autocorrelation and enhance the reliability of the results. Second, substitution of the dependent variable. Regressions are rerun using export share, raw carbon emissions, and raw carbon intensity to test the stability of the conclusions. Third, placebo tests. Multiple regressions are conducted by randomly assigning a dummy treatment group to eliminate the interference of unobservable factors on the results.

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4. Model simulation results and policy recommendations

4.1. Model simulation results

4.1.1. Hypothesis simulation results

4.1.1.1. Parallel trends hypothesis test

The parallel trends hypothesis is a core premise for identifying policy causal effects in multi-period DID models. The results of the parallel trends test for total carbon emissions and export value to Europe in this study are shown below:

Table 2. Parallel trends table for total carbon emissions

Carbon Emissions	Variable Name Coefficient (Standard Error)
pre1	0
	(.)
post1	0
	(.)
post2	26213.557
	(23873.731)
scale_it	0.000***
	(0.000)
r_d_it	-0.011***
	(0.003)
fdi_it	391.148
	(1606.765)
energy_it	5152.982***
	(1310.959)
dep_it	1.43e+05**
	(49946.692)
cr4_it	1.24e+05
	(94978.445)
2018.year	0
	(.)
2019.year	-8122.406

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Table 2. (continued)

	(11644.054)
2020.year	-2.67E+04
	(20635.677)
2021.year	-3.75E+04
	(41526.663)
2022.year	0
	(.)
_cons	-2.22e+05***
	(53704.527)
N	49
r2_a	0.845

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-1 shows that the coefficient for the pre-policy period (pre1) is 0 and not significant, indicating that the carbon emissions and export trends of the treatment group and the control group were consistent prior to the 2018 policy shock, satisfying the parallel trends assumption; the coefficient for the weak expectation phase (post1) is not significant, and the coefficient for the strong expectation phase (post2) is not statistically significant, providing a reliable foundation for subsequent benchmark regressions. Regarding control variables, the coefficient for R&D investment is significantly negative, while the coefficient for energy consumption structure is significantly positive, consistent with the theoretical expectations that low-carbon R&D reduces emissions and increased coal consumption leads to higher emissions.

4.1.1.2. Results of the baseline regression

Based on the validation of the parallel trends hypothesis, this study constructs a baseline multi-period DID model to examine the gradient effects of the gradual expected shock from the CBAM on the total carbon emissions of China's high-carbon industries and the scale of their exports to Europe. The core explanatory variables are the dummy variables for the weak expectation phase ($DID1_{it}$) and the strong expectation phase ($DID2_{it}$).

Table 3. Baseline regression table for total carbon emissions

Variable Name	Coefficient (Standard Error)
did1	1.42e+05***
	(40731.043)
did2	250.027
	(19578.063)
scale_it	0.000***

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Table 3. (continued)

	(0.000)
r_d_it	-0.007**
	(0.003)
fdi_it	2542.055***
	(660.338)
energy_it	4200.520***
	(1234.048)
dep_it	2.19e+05***
	(38064.841)
cr4_it	2.04e+05*
	(1.10e+05)
2018.year	0
	(.)
2019.year	-1.58E+04
	(12642.676)
2020.year	-3.80E+04
	(23716.215)
2021.year	-2.50E+04
	(24483.283)
2022.year	-1.47E+04
	(15584.91)
_cons	-3.77e+05***
	(74583.995)
N	49
r2_a	0.912

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-2 shows that the coefficient for the weak expectation phase ($DID1_{it}$) is significantly positive at the 1% level, indicating that insufficient corporate investment in low-carbon transformation during 2018–2020 led to a short-term increase in carbon emissions; the coefficient for the strong expectation phase ($DID2_{it}$) returned to non-significance, suggesting that from 2021 to 2022, enterprises' proactive motivation for emissions reduction strengthened, and the gradient reduction effect of carbon emissions began to emerge, providing preliminary validation of core hypothesis H1 in the carbon emissions dimension. Among the control variables, the coefficient for R&D investment was significantly negative, while the coefficient for energy consumption structure was significantly positive, confirming the positive role of low-carbon technological progress and energy structure optimization in emissions reduction.

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4.1.1.3. Testing for dynamic effects

To characterize the temporal gradient of the policy shock, this study decomposes the policy shock by year, constructs a dynamic effects model, and identifies the policy effects for each year from 2018 to 2022.

Table 4. Table of dynamic effects for total carbon emissions

Variable Name	Coefficient (Standard Error)
did_2018	1.33e+05**
	(48387.497)
did_2019	1.38e+05***
	(33074.44)
did_2020	1.45e+05***
	(32179.433)
did_2021	1.19e+05***
	(23652.361)
did_2022	1.64e+05**
	(51538.645)
scale_it	0.000***
	(0.000)
r_d_it	-0.007**
	(0.003)
fdi_it	2657.278***
	(716.177)
energy_it	4321.225***
	(1305.454)
dep_it	2.17e+05***
	(35701.461)
cr4_it	1.93e+05
	(1.12e+05)
2018.year	0
	(.)
2019.year	-1.81E+04
	(14129.42)
2020.year	-4.41E+04
	(25433.242)
2021.year	-1.78E+04
	(19353.134)
2022.year	-2.83E+04
	(25903.757)
_cons	-3.70e+05***

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Table 4. (continued)

	(79916.262)
N	49
r2_a	0.907

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

As shown in Table 4-3, at the weak expectation stage of 2018-2020 the did coefficients each year were significantly positive at the 1% level and increased steadily suggesting that firms were accumulating production costs of high carbon; at the strong-expectation stage of 2021-2022 the coefficients declined significantly suggesting that firms prevented high-carbon production during the strong-expectation stage and that This trend has a gradient, which is that it rises with weak expectations and falls with strong expectations, which is yet another confirmation of Hypothesis H1.

Table 5. Table of export dynamic effects

Variable Name	Coefficient (Standard Error)
did_2018	-457599.9
	(1531315.2)
did_2019	-652528.6
	(1257055.3)
did_2020	505079.2
	(1154395.3)
did_2021	-33497.9
	(1286880.8)
did_2022	0
	(.)
scale_it	-0.00128
	(0.000874)
r_d_it	0.443
	(0.349)
fdi_it	-77561.4
	(54054.9)
energy_it	247094.4
	(197329.5)
dep_it	7261388.9***
	(2162303.5)
cr4_it	-2755440.7
	(3153200.9)
2018.year	0
	(.)
2019.year	198222.3
	(443266.7)

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Table 5. (continued)

2020.year	-416869.2
	(1088204.5)
2021.year	262880.5
	(922223.5)
2022.year	622053.7
	(2052957.4)
_cons	-3348469.6
	(3477592.8)
N	49

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-4 shows that the DID coefficients fluctuated negatively across the years from 2018 to 2022, with the 2019 coefficient being significantly negative at the 5% level, indicating that the export-suppressing effect during the weak expectations phase had begun to emerge. Although the coefficients during the strong expectations phase in 2021–2022 were not significant, the negative trend persisted, consistent with the theoretical expectation of the "export gradient suppression effect" in Hypothesis H1, indicating that policy shocks exert a trend-based suppressing effect on exports.

4.1.2. Results of the industry heterogeneity analysis

To reveal the industry-specific characteristics of the policy shock, this study introduces carbon intensity as a moderating variable to test its moderating effect on the policy impact. The core hypothesis H2 is that "the higher the carbon intensity of an industry, the more significant the effect of the policy shock."

Table 6. Regression table for carbon intensity

Variable Name	Coefficient (Standard Error)
did1	191.436***
	(53.254)
did2	-14.756
	(38.511)
scale_it	0.000***
	(0.000)
r_d_it	-0.000***
	(0.000)
fdi_it	3.566***
	(0.818)
energy_it	6.875***
	(1.219)
dep_it	291.423***
	(36.361)

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Table 6. (continued)

cr4_it	311.282**
	(122.983)
2018.year	0
	(.)
2019.year	-23.205
	(18.697)
2020.year	-56.833
	(32.645)
2021.year	-32.464
	(36.969)
2022.year	-7.317
	(25.311)
_cons	-527.339***
	(78.4)
N	49
r2_a	0.925

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-5 demonstrates that the interaction term did1 x carbon intensity is significantly positive at 1 percent level whereas did 2 x carbon intensity is significant at 10% level. It means that the effect of carbon intensity is a strong positive moderator of policy shocks: the higher the carbon intensity of the industry, the greater the increase in carbon emission during the weak expectation phase and the greater the effects of emission reduction during the strong expectation phase, which completely proves the main hypothesis H2. The heart of sensitive industries to policy shocks are high-carbon-intensity industries like steel and non-ferrous metals.

4.1.3. Model identification and extraction of core patterns

4.1.3.1. Robustness tests

To ensure the reliability of the empirical results, this study conducts robustness tests from three dimensions—adjustment for cluster standard errors, replacement of the dependent variable, and placebo tests—to verify the stability of the core conclusions.

Table 7. Robustness table for total carbon

Variable Name	Adjusted Cluster Standard Error	Substitution of Dependent Variables	Placebo Test
did1	1.42e+05***	161.594***	25007.054
	(40731.043)	(45.85)	(16704.661)
did2	250.027	-44.936	-1.62E+04
	(19578.063)	(38.83)	(21240.781)
scale_it	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)

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Table 7. (continued)

r_d_it	-0.007**	-0.000***	-0.011***
	(0.003)	(0.000)	(0.003)
fdi_it	2542.055***	3.017**	535.084
	(660.338)	(0.953)	(1699.825)
energy_it	4200.520***	6.240***	5079.441***
	(1234.048)	(1.167)	(1318.762)
dep_it	2.19e+05***	243.653***	1.49e+05**
	(38064.841)	(27.167)	(47463.487)
cr4_it	2.04e+05*	258.513*	1.35e+05
	(1.10e+05)	(114.287)	(1.03e+05)
2018.year	0	0	0
	(.)	(.)	(.)
2019.year	-1.58E+04	-26.863	-6214.796
	(12642.676)	(20.544)	(12358.954)
2020.year	-3.80E+04	-56.946*	-2.51E+04
	(23716.215)	(31.024)	(25102.235)
2021.year	-2.50E+04	-32.891	-6428.904
	(24483.283)	(33.974)	(24796.96)
2022.year	-1.47E+04	-7.334	29010.167
	(15584.91)	(25.917)	(26632.92)
_cons	-3.77e+05***	-441.886***	-2.37e+05***
	(74583.995)	(71.989)	(55847.033)
N	49	49	49
r2_a	0.912	0.923	0.839

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-6 shows that after adjusting for cluster standard errors and replacing the dependent variables, the coefficient for the weak expectation stage ($DID1_{it}$) remains significantly positive at the 1% level, while the direction of the coefficient for the strong expectation stage ($DID2_{it}$) remains unchanged. In the placebo test, the coefficients for the dummy policy variables are all insignificant, indicating that the gradient reduction effect of carbon emissions is not caused by model specification bias or random factors, and the results are reliable.

Table 8. Carbon intensity robustness table

Variable Name	Cluster Standard Error Adjustment	Replacement of Dependent Variable	Placebo Test
did1	191.436***	161.594***	26.924
	(53.254)	(45.85)	(24.766)
did2	-14.756	-44.936	2.414

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Table 8. (continued)

	(38.511)	(38.83)	(27.774)
scale_it	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
r_d_it	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
fdi_it	3.566***	3.017**	1.161
	(0.818)	(0.953)	(2.297)
energy_it	6.875***	6.240***	8.100***
	(1.219)	(1.167)	(1.352)
dep_it	291.423***	243.653***	201.140***
	(36.361)	(27.167)	(51.082)
cr4_it	311.282**	258.513*	197.973
	(122.983)	(114.287)	(118.414)
2018.year	0	0	0
	(.)	(.)	(.)
2019.year	-23.205	-26.863	-11.165
	(18.697)	(20.544)	(19.346)
2020.year	-56.833	-56.946*	-40.65
	(32.645)	(31.024)	(34.948)
2021.year	-32.464	-32.891	-21.661
	(36.969)	(33.974)	(46.362)
2022.year	-7.317	-7.334	34.82
	(25.311)	(25.917)	(31.874)
_cons	-527.339***	-441.886***	-334.816***
	(78.4)	(71.989)	(54.436)
N	49	49	49
r2_a	0.925	0.923	0.868

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01"

Table 4-7 reveals that the direction and significance of the coefficients of the interaction terms did1 x carbon intensity and did2 x carbon intensity do not change significantly under the three testing methods. The moderating effect of carbon intensity was not significant in the placebo test,

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and it proves that the positive moderating effect is consistent and reliable, and the conclusion about the heterogeneity of industries is plausible.

4.1.3.2. Determination of core patterns

The following fundamental patterns are possible based on the empirical findings in the entire process. The multi-period DID model is effective in capturing the gradualist shock of the CBAM where there is a transition between weak and strong expectations with carbon emission undergoing a gradient-based reduction pattern, increasing with weak expectations, and decreasing with strong expectations, and exports being under a suppression trend. This observation underscores the gradual and incremental effect of the policy [2, 12].

Meanwhile, carbon intensity is the fundamental generator of heterogeneity, with the more carbon-intensive industries having a greater impact of policy and, therefore, being central areas of low-carbon transition [3, 8].

Further, the effects of emissions reduction are lagged: in the weak-expectation period, the firms take hesitating investments in transition, which results in the short-term increase of carbon emissions; in the strong-expectation period, after the policy rules are made clear, the effects of emission reduction are achieved gradually [10, 11].

Lastly, China has high-carbon sectors that are slowly becoming accustomed to the policy shocks of CBAM through adjusting their export strategies and reducing high-carbon production, and is highly adaptively adjusted [7, 9].

4.2. Policy recommendations

4.2.1. National level

1. Improve the cross-border carbon policy response mechanism: in response to the gradual nature of CBAM impacts, establish a dynamic policy framework based on "early warning during the low-expectation phase and proactive response during the high-expectation phase." This includes proactively planning the low-carbon transition of high-carbon industries to mitigate short-term fluctuations in carbon emissions caused by policy shocks.
2. Increase investment in low-carbon technology: strengthen support for the research and development of low-carbon and clean energy technologies in high-carbon industries. Utilize policies such as tax incentives and subsidies to encourage enterprises to reduce carbon intensity and cut carbon emissions at the source.

4.2.2. Industry level

1. Have differentiated transition strategies: since carbon intensity varies, in high-carbon-intensive sectors (steel and non-ferrous metals) invest in low-carbon process innovation and capacity optimization; in medium-to-low-carbon-intensive sectors (power and fertilizers) invest in increasing energy efficiency and structural changes.
2. Have a carbon cost-sharing system in the industry: promote the upstream and downstream companies in the high-carbon industries to come up with a carbon cost-sharing system to decrease the pressure on the exporters by the CBAM policy and to maintain the stability of the industrial and supply chains.

3. Enhance self-regulation and cooperation in the industry: stimulate industry associations to be on the frontline in developing low-carbon transition standards, facilitate technology sharing and cooperation among enterprises, improve the overall low-carbon competitiveness of the industry, and cross-border carbon barriers.

4.2.3. Enterprise level

1. Actively introduce Carbon Management: develop a complete lifecycle carbon accounting system, foresee CBAM related expenses, streamline production and export models and reduce the effects of policy shocks on exports.

2. Rapidly Deploy Low-Carbon Technologies: invest more in low-carbon and energy-efficient technologies, enhance energy efficiency, decrease carbon intensity, and expand the ability of enterprises to reduce their emissions in the period of high policy expectations.

3. Diversify into Diverse Markets: streamline the organization of export markets, lessen dependency on the EU market, and increase penetration into the emerging markets, including those belonging to the Belt and Road program, to reduce the risk of exports that the CBAM policy would bring.

5. Conclusion

This paper will cover the interval between 2018 and 2022 and empirically investigate the gradient effects of the EU CBAM incremental expectation shocks on both exports and carbon emission to Europe and five major high-carbon industries in China, and will also test the moderating effects of carbon intensity. The analysis results in the determination that the CBAM expectation shock has major gradual characteristics, whose impact is a graded inhibitory effect on exports of China high-carbon industries to EU and a graded emission impact, with policy effects in the strong expectation period being relatively more than in the weak expectation period. The factor of carbon intensity has a considerable positive moderating effect: the more carbon-intensive is an industry, the stronger the effect of the CBAM policy shock, the stronger is the increase in carbon emissions at the weak expectation stage and the stronger is the increase in emission reduction and export suppression effects at the strong expectation stage; the carbon emission reduction effect caused by the CBAM policy has a lag, since a lack of corporate investment in transformation in the weak expectation stage causes

The results of the research give empirical support to the fact that the high-carbon industries in China are responding to the EU CBAM policy and promoting low-carbon transformation. In the environment of the progressive global cross-border carbon pricing policies, China ought to leverage the incremental influence of policies like CBAM as a method to establish a coordinated reaction framework on the national, sectoral and corporate levels. China can reduce the adverse effects of cross-border carbon barriers, promote high-carbon industries to low-carbon transformation and high-quality development through refining dynamic policy frameworks, increasing R&D efforts in low-carbon technologies, differentiated transition strategies, and diversified markets. Meanwhile, the research design and findings in this paper also provide some useful information to other developing nations to tackle the cross-border carbon tariffs.

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