Environmental Policy Coordination *

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Abstract

This paper studies how carbon policies in the EU lead to inadvertent environmental regulation adjustments in China. Using a novel dataset containing the universe of Chinese environmental penalties and a comprehensive measure of sectoral carbon costs in Europe, we employ a shift-share measure of the exposure to EU carbon price costs among Chinese cities for identification. We find that higher exposure to export-weighted carbon prices has a sizeable positive impact on environmental regulation stringency. Conversely, industries more reliant on imports from the EU receive slightly fewer penalties. We attribute the stricter policies in Chinese cities primarily to the surge in exports and associated pollution resulting from EU carbon policies. Further empirical analysis shows that increased enforcement is targeted at tradable sectors rather than a city-wide policy switch. However, when local officials adopt more lenient regulations toward sectors adversely affected by higher EU carbon costs, they compensate by imposing more penalties on non-tradable sectors. Our study contributes to the debate on optimal unilateral carbon and trade policies by offering new insights into how domestic carbon pricing can trigger passive environmental policy responses abroad, highlighting the complexities of global environmental policy interplay.

Keywords: Environmental Regulation in China, Policy Coordination, Carbon Price, EU ETS

JEL Codes: Q56, Q58, F18, F64, O13

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1 Introduction

Climate change represents an existential challenge for all nations, with significant global economic, environmental, and social consequences. As extreme weather events become more frequent and costly, the urgency for coordinated action is clear. While efforts to establish a global unified response have largely failed, countries have turned to unilateral carbon policies as a second-best solution.

However, a significant concern about carbon leakage arises when production shifts from countries with strict carbon regulations to those with more lenient standards. This phenomenon offsets emission reduction efforts, making the effectiveness of such policies questionable. In response, substantial research has explored how optimal combinations of domestic carbon policies and trade policies can mitigate the distortions arising from unilateral measures (Kortum and Weisbach, 2023; Farrokhi and Lashkaripour, 2024). One prominent solution proposed is the carbon border adjustment mechanism, designed to equalize the carbon costs of imported goods with those of domestically produced ones [1].

Among the extensive theoretical work on designing optimal policy responses, one common assumption is that only the home country enforces carbon policies, with no carbon policies or at least no policy responses from foreign countries(Markusen, 1975; Böhringer et al., 2014; Kortum and Weisbach, 2023). This assumption overlooks the potential for international policy interplay, where domestic carbon pricing might prompt foreign governments to adjust their own environmental regulations, passively or strategically, too.

In this paper, we empirically investigate whether unilateral carbon policies in one major economy can lead to unintended spillover effects on environmental regulation in another. Specifically, we examine how increased carbon costs in the EU, as part of its Emissions Trading System (ETS), influence environmental regulation decisions by local officials in China, using data from 2000 to 2020. By leveraging a measure of the city-sector-level exposure to EU carbon prices and analyzing a novel dataset on Chinese environmental penalties, we shed light on the cross-border effects of carbon policies and provide new insights into the dynamics of international environmental regulations.

We construct a shift-share measure of EU carbon price exposure at the Chinese city-sector level, using the pre-EU ETS sectoral export (or import) ratio as the share and the

[1] An early example is California's border carbon adjustment system, initiated in 2013, which requires electricity importers from other states to account for emissions generated elsewhere. Another notable example is the European Union's Carbon Border Adjustment Mechanism (CBAM), commencing in 2026, mandating importers to report and pay for carbon emissions embodied in imported products covered by the EU Emissions Trading System (EU ETS) (Fontagné and Schubert (2023)).

varying common embodied sectoral carbon costs, including both direct carbon costs and the indirect carbon costs through the supply chain, in the EU as the shift. To do this, we utilize data from the EXIOBASE project, which provides multi-regional input-output tables, along with detailed sectoral carbon prices obtained from Resources for the Future (RFF) (Dolphin and Xiahou, 2022). Additionally, we leverage the Chinese customs dataset provided by the General Administration of Customs, which includes the universe of Chinese international transactions, to calculate the fixed sectoral export (or import) ratios with EU countries.

These measures of exposure to EU carbon prices act as plausibly exogenous shocks, helping us causally identify the impacts of higher carbon prices in the EU on local environmental regulations in China. We can also use this shift-share measure to identify its impacts on total export, total import, and environmental outcomes to explore the mechanisms behind these passive policy responses. The validity of the causal identification and consistency of the estimates of our empirical strategy relies on the exogeneity of the shares or shifts (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). We claim that the varying sectoral carbon costs in the EU between 2005 and 2020, which mainly capture changes in carbon prices in the EU, are exogenous to city and city-sector level outcomes in China. Moreover, we discuss other threats to identification in Section 4 and also use an alternative measure of the EU carbon price, which excludes impacts of economic status, to address the endogeneity concerns further.

We use a novel dataset containing the universe of Chinese administrative environmental penalties to measure the environmental regulation stringency among Chinese local officials, along with data sources to measure sectoral trade and environmental outcomes. Our findings indicate that higher export-weighted exposure to EU carbon prices is associated with more stringent environmental regulation in China, evidenced by increased frequency of environmental penalties and higher penalty amounts. Conversely, higher import-weighted exposure to EU carbon prices leads to slightly more lenient environmental regulation, suggesting a potential balancing act by local officials to mitigate adverse input cost effects. Further analysis reveals that higher export-weighted EU carbon costs also lead to increased sectoral exports, higher emissions, and elevated $PM_{2.5}$ levels, while higher import-weighted exposure results in increased import values, higher import unit prices, lower emissions, and reduced pollutants.

These findings imply that local Chinese officials adjust environmental regulations to respond to higher environmental pressure induced by increased exports and also to slightly support firms more reliant on EU imports with fewer penalties. This policy response can either be targeted or city-wide, while heterogeneity analysis shows that stricter regulations are only targeted at tradable sectors with more benefits from higher export demands. However, there is suggestive evidence showing that while local Chinese officials have more lenient environmental regulations on tradable sectors, with cities experiencing more import-induced EU carbon cost pressure, stricter measures are observed on non-tradable sectors, implying a strategic response by local officials to balance overall environmental outcomes.

The dynamic analysis also shows the impulse response of main outcomes on varying exposure to carbon cost change in the EU. Higher export-weighted exposure to the EU carbon costs lead to an immediate and strong response on environmental penalties, and also quick and large responses on sectoral export values, export volumes, and persistent increases in wastewater and PM2.5 density. Similarly, import-weighted exposure to higher EU carbon prices causes immediate and insignificant rises in environmental regulation stringency, immediate and large increase in imports, and persistent and strong decreases in major pollutants and carbon emissions.

Multiple robustness checks using different specifications, including alternative fixed effects, lagged independent variables, different weights in the shift-share measures, and alternative carbon price measures, provide consistent results on the associations between carbon policies in the EU and local environmental regulations in China. Our findings challenge the assumption that unilateral carbon policies have no spillover effects on foreign environmental regulations. Instead, we demonstrate that such policies can induce passive environmental regulation adjustments abroad, suggesting that the scale of carbon leakage is not as large as what researchers used to estimate. Furthermore, these findings contribute to the design of optimal trade policy to mitigate carbon leakage.

Related literature and contributions This paper contributes to several strands of literature. First, it is connected to the literature on international policy coordination, particularly in the context of environmental policies. Several theoretical studies have highlighted the potential benefits of international coordination of macroeconomic policies, including environmental measures (Oudiz and Sachs, 1985; Fischer, 1987; Ederington, 2001; Canzoneri et al., 2005). More recent work has shifted towards understanding why coordination is infrequent, despite the apparent gains, focusing on factors such as differences in country size, economic conditions, policy objectives, and the externalities associated with unilateral policies (Ostry and Ghosh, 2016; Bhattarai et al., 2021; Trein et al., 2021).

There is also a growing body of literature examining international environmental policy coordination, particularly focusing on the conditions under which coordination is feasible and beneficial and the role of policy spillovers (Hoel, 1997; Ulph and Maddison, 1997; Finus et al., 2013; Bayham et al., 2019; Kollenbach and Schopf, 2022; Cadoret and Padovano, 2024). Two recent papers, Zhou (2023) and Hsiao (2024), are particularly relevant. Zhou (2023) shows that import restrictions on environmentally harmful goods in China can lead to similar restrictions in other cities due to spillover effects. In contrast, Hsiao (2024) demonstrates that coordinated import tariffs can achieve much of the effectiveness of domestic environmental taxes. Our paper extends this literature by providing empirical evidence of passive international policy coordination induced by unilateral carbon policies. We show that carbon policies in the EU can influence local environmental regulation in China through spillover effects at the cross-nation level.

Second, our work contributes to the literature on the relationship between trade, the environment, and carbon leakage. Existing studies have documented the effects of economic growth and trade on environmental outcomes, including the environmental Kuznets curve, which posits that environmental degradation first increases and then decreases with economic growth (Grossman and Krueger, 1995; Copeland and Taylor, 2004; Cristea et al., 2013; Shapiro, 2021; Copeland et al., 2021; Felbermayr et al., 2022). The concept of carbon leakage has also been extensively studied, with empirical evidence showing that trade can undermine the effectiveness of carbon policies by shifting production to countries with lower carbon costs (Schroeder and Stracca, 2023; Laeven and Popov, 2023; Li et al., 2024; Känzig et al., 2024). Our findings contribute to this literature by providing a new piece of direct evidence on carbon leakage.

Third, our paper informs the design of optimal unilateral carbon and trade policies. Theoretical literature proposes various strategies to combat climate change in the absence of a unified global carbon market, such as carbon border taxes, climate clubs, and green subsidies (Nordhaus, 2015; Thivierge, 2023; Kortum and Weisbach, 2023; Fontagné and Schubert, 2023; Weisbach et al., 2023; Blanchard et al., 2023; Farrokhi and Lashkaripour, 2024). These theoretical works often assume that only the home country enacts carbon policies. Our findings demonstrate that unilateral carbon policies can provoke environmental policy responses abroad, adding a new dimension to future theoretical analysis of optimal policy design.

Fourth, we contribute to the empirical evaluation of the EU ETS. While previous research has focused on the EU ETS's impact on European firm-level activities, emissions, productivity, and macroeconomic outcomes (Känzig and Konradt, 2023; Känzig, 2023; Wang, 2024; Colmer et al., 2024), few studies have examined its spillover effects on other countries. We fill this gap by showing that the EU ETS influences environmental regulation in China, the world's largest exporter and carbon emitter, providing new insights into the global implications of this major carbon pricing initiative.

This paper also contributes to the growing literature on the local enforcement of environmental regulations. While the design of environmental regulations is important, their effectiveness often depends on the enforcement at the local level (Buntaine et al., 2024). Compared to the design of environmental regulations, local enforcement tends to be more flexible depending on local factors. For instance, Limited enforcement capacity can lead to targeting strategies, such as focusing only on highly-polluting plants (Duflo et al., 2018). Additionally, local regulators face trade-offs between economic development and pollution reduction, which may drive strategic behaviors like targeting plants located upstream or upwind of pollution monitors (He et al., 2020; Xie and Yuan, 2023; Yang et al., 2023) or strategically shutting down monitors (Zou, 2021; Mu et al., 2024). This paper provides new evidence on when local regulators choose to enhance enforcement, extending beyond purely political motivations (Kahn et al., 2015; Wang and Wang, 2020; Kong and Liu, 2023).

Lastly, this paper expands the application of shift-share instruments in measuring local exposure to trade-related shocks (Autor et al., 2013; Dix-Carneiro and Kovak, 2015; Dai et al., 2020, 2021). By constructing city-sector-level measures of EU carbon price exposure, we provide a methodological contribution that can be applied to other contexts involving international policy spillovers.

Outline The remainder of the paper is structured as follows. Section 2 provides institutional background on carbon policies in Europe and environmental regulations in China. Section 3 describes the data sources and presents descriptive evidence. Section 4 outlines the methodology for measuring carbon price exposure and the identification strategy. Section 5 presents the main regression results. Section 6 discusses the mechanisms behind the observed policy coordination. The final section concludes the paper.

2 Institutional Background

2.1 Carbon Policies in Europe

Established in 2005, the European Union Emissions Trading System (EU ETS) is the cornerstone of the EU's climate policy and the world's first and largest cap-and-trade carbon market. It covers over 12,000 installations in the energy and manufacturing sectors and aircraft operators flying within the EU and to Switzerland and the United Kingdom (UK). The EU ETS accounts for approximately 40 percent of Europe's greenhouse gas emissions and 5 percent of global emissions (Känzig and Konradt, 2023). As a cap-and-trade system, the EU ETS sets an annually decreasing cap on total greenhouse gas emissions.[2] Under this cap, companies receive or purchase emission allowances through auctions, which they can trade in the market. Firms are required to monitor and report their annual emissions and surrender enough allowances to cover their total emissions each year.

The EU ETS applies to all 27 EU member states, including the UK, until its departure in 2021, as well as Iceland, Liechtenstein, and Norway through the European Economic Area (EEA) agreement and Northern Ireland for electricity generation. Since 2020, the Swiss Emissions Trading System has been linked to the EU ETS. UK companies were participants in the EU ETS during the whole time interval of our study in this paper [3] Therefore, we include the corresponding yearly average carbon prices for UK sectors throughout our study period. We also account for changes in carbon pricing applicable to Swiss sectors participating in the Swiss ETS due to its linkage with the EU ETS since 2020 and the close economic ties between the EU and Switzerland.

Carbon Price Dynamics of the EU ETS The EU ETS allows companies to trade surplus EU allowances (EUAs) in the market, with the average yearly price of EUAs in spot and futures markets reflecting the balance of supply and demand. The EU ETS has evolved throughout its different trading phases by adjusting the annual emission cap, shifting from free allocation to auctioning allowances, expanding coverage to include additional gases and sectors, introducing international credits, and establishing a market stability reserve. These policy adjustments have influenced carbon prices (Känzig, 2023) and signify the EU's commitment to mitigating climate change.

Figure 1 illustrates the time trend of the EU ETS carbon price from 2005 to 2020. The first period of the EU ETS price trajectory was from 2005 to 2007, corresponding to phase one of the trading regime. The carbon price dropped largely from 2005 to 2007 since the

[2]Currently in its fourth trading phase (2021–2030), the EU ETS reduces the emission cap linearly by 2.2% each year.

[3]The new UK Emissions Trading Scheme (UK ETS), which replaced the UK's participation in the EU ETS on January 1, 2021, operates similarly. Although the UK ETS began on January 1, 2021, British companies were required to comply with the EU ETS until the end of the scheme year in April 2021. Consequently, the UK carbon market did not open for trading until May 2021. The UK ETS closely mirrors the EU ETS in terms of coverage and operational structure, with the main difference being a slower rate of emission cap reduction compared to the EU ETS starting from 2024.

total allowances were too high, and the price went to zero since the extra allowances could not be transferred to the next phase. The phase two of the EU ETS regime was from 2008 to 2012. Despite the overall regulatory events meant to raise the carbon price, including fewer free allowances and more auctions happening, declining annual emission caps, and increasing sectoral coverages, the caps were still higher than needed, mostly due to the 2008 financial crisis and the EU ETS carbon price remained at a moderate level. The more recent phase 3 of the EU ETS trading regime was from 2013 to 2020, parallel with a steadily increasing price. This trajectory of rising prices was mainly due to further stricter carbon policies regarding the EU ETS, including the start of the EU-wide cap requirements and the market stability reserve, as well as broader sector and gas coverage [4]. Hence, the trajectory of the EU ETS carbon prices is a feasible indicator of the stringency of carbon policies in the EU. However, we restrict our analysis until the end of 2020 to minimize the impacts of the Coronavirus disease 2019 (COVID-19) pandemic, as well as the unusual surge of the EU ETS carbon price since 2021 due to the economic recovery and Russian invasion of Ukraine. In Section 5.5, as a robustness check, we show the regression results containing our latest available data source until the end of 2023.

Other Climate Policies in Europe In addition to the EU ETS, European countries have implemented other climate policies, such as carbon taxes, the forthcoming EU ETS2, and the EU's Carbon Border Adjustment Mechanism (CBAM). Some European countries impose carbon taxes on sectors not covered by the EU ETS to avoid double taxation. Moreover, the EU ETS2 is a new emissions trading system scheduled to commence in 2027, covering emissions from fuel combustion in buildings, road transport, and other sectors currently outside the scope of the EU ETS. The CBAM, set to start in 2026, is designed to address carbon emissions embedded in imported goods by requiring EU importers to declare these emissions and surrender corresponding carbon emission allowances annually. Since carbon taxes generally apply to non-tradable sectors and other carbon mechanisms are not yet in effect, our analysis focuses exclusively on the EU ETS and its carbon price trajectory.

2.2 Environmental Policies and Enforcement in China

China's GDP grew by 588% in the two decades following the Reform and Opening in 1978, driven primarily by industrial manufacturing, which resulted in significant air and water

[4] Also see Känzig (2023) and Ellerman et al. (2016) for more detailed descriptions of the history of EU ETS's phases

pollution. According to the World Health Organization (WHO), outdoor air pollution contributed to an estimated 300,000 premature deaths annually in China (Cohen et al., 2005).

Since the early 1990s, a range of environmental regulations has been introduced in China to address the rising pollution problems. The two main regulatory tools are emission standards and pollutant discharge permits. The Chinese Ministry of Environmental Protection (MEP) sets and periodically updates sector-specific emission standards. Pollutant discharge permits were introduced in 2003, requiring polluting firms to purchase permits for their emissions. In 2018, these permits evolved into an emissions tax[5].

Environmental regulations in China are typically established by central or provincial governments but often lack detailed guidelines for enforcement and inspections. This gives local regulators at the prefecture or lower levels significant flexibility in deciding how to enforce these regulations. They hold the authority to shut down non-compliant firms or impose environmental fines. However, local officials were historically evaluated for promotion based on GDP growth. Under the trade-offs between promoting economic growth and enforcing environmental regulations, these regulations were often loosely applied. As shown in Figure 3, despite rising emissions from industrial sectors, local regulators issued few penalties before 2010, even with environmental regulations in place.

To incentivize local officials to take action against pollution, the central government introduced a series of reforms, including changes to political incentives and improvements in monitoring. In 2005, the central government altered promotion criteria, which had previously been based solely on economic growth. After the reform, local officials were required to meet specific environmental targets to be eligible for promotion. Once those targets were achieved, economic growth performance determined the likelihood of promotion. Kahn et al. (2015) demonstrated that local officials nearing the age threshold for promotion were motivated to reduce water pollution more actively.

In addition to these political incentives, the central government enhanced environmental governance through centralization. In 2016, the Ministry of Environmental Protection (MEP) reformed the personnel appointment process, transferring the authority to appoint prefectural MEP directors from the local governments, headed by mayors and city secretaries, to the provincial MEP. This reform reduced the economic pressures on local regulators tied to promotion concerns from mayors and city officials, which allowed for stricter enforcement of environmental regulations. Kong and Liu (2023) found that this reform

[5] Pollutant discharge permits were managed by the MEP at the local level. The responsibility for collecting emissions taxes was transferred to local Tax Bureaus in 2018.

significantly increased both the number and amount of fines issued by local regulators, leading to significant improvements in environmental quality.

Furthermore, to address the principal-agent problem between the central government and local regulatory enforcement, the central government significantly enhanced pollution monitoring and data collection. The Ministry of Environmental Protection (MEP) began rolling out pollution monitors nationwide in 2014 and required plants in high-emission industries to install Continuous Emissions Monitoring Systems (CEMS) as early as 2007. By 2020, over 1,600 pollution monitors were installed across 367 Chinese cities. Additionally, by the end of 2013, 14,410 firms had integrated into the system, continuously uploading hourly, pollutant-specific emission data to an online platform accessible at the provincial level. This use of technology has markedly improved regulatory enforcement and improved to air quality (Greenstone et al., 2022).

Despite political incentives and enhanced monitoring from the central government, local enforcement of environmental regulations remains incomplete, largely due to the persistent trade-offs between economic growth and environmental protection. Local regulators have been found to strategically target polluting plants located upstream or upwind of pollution monitors (He et al., 2020; Xie and Yuan, 2023; Yang et al., 2023) in order to improve monitor readings without fully addressing broader pollution issues. This paper will investigate whether economic shocks induced by EU carbon policies can influence and shift local enforcement of environmental regulations.

3 Data Source

This paper utilizes data from various sources, including sector-specific carbon prices within EU countries, the UK, and Switzerland each year, input-output tables for each year within the EU, detailed customs data from China, city-level environmental outcomes such as major total pollutants emissions and yearly average PM2.5 levels, and detailed environmental regulation events and penalty data of cities in China.

3.1 Carbon price in Europe

The carbon price data at the sector level that we use is from the World Carbon Pricing Database compiled by Resources for the Future (RFF)[6] (Dolphin and Xiahou, 2022). The database provides information on the coverage and rates of both cap-and-trade allowances and carbon taxes on the sector-fuel levels in 201 jurisdictions from 1990 to 2022, and it is so far the most comprehensive resource for carbon price regimes with rich coverage in both jurisdictions and sectors. All carbon prices across years and countries are converted into 2015 Euros per ton of CO_2 equivalence. Additional details about the sector disaggregation standards, sector concordance, and data sources of this database can be found in the appendix.

3.2 Global Input-Output Table

We require a global input-output table to calculate the total carbon price exposure, including both direct and indirect costs, of a specific industry within the EU. We use data from Exiobase[7] (Stadler et al., 2018). The latest Exiobase version 3 provides detailed input-output tables from 2000 to 2020 and the direct CO2 emissions of each industry and country pair, sourced from the International Energy Agency (IEA). Exiobase covers 44 countries, including all 27 EU countries, the UK, Switzerland, and 15 other major economies. It contains 200 products and 163 industries. There are several other global input-output database available, including the World Input-Output Database (WIOD)[8], the OECD Input-Output Tables database (OECD IOTs) [9], and the Eora multi-region input-output table (Eora MRIO)[10]. The Exiobase environmentally-extended multi-region input-output (EE MRIO) tables are widely used for analyzing global environmental trade-related issues (Shapiro, 2021; Wang, 2024). In our case, Exiobase is preferred due to its coverage of additional sectors and their corresponding direct carbon emissions. Furthermore, Exiobase has been developed through projects supported by the European research framework programs, making it particularly suitable for studying the carbon policies within the EU (Wang, 2024). Details of sectors, data structure, and sector concordance process can be found in the appendix.

[6] https://www.rff.org/publications/data-tools/world-carbon-pricing-database/, and the database is hosted here: https://github.com/g-dolphin/WorldCarbonPricingDatabase

[7] The homepage of Exiobase: https://www.exiobase.eu/index.php/about-exiobase

[8] The homepage of WIOD: https://www.rug.nl/ggdc/valuechain/wiod/

[9] The homepage of OECD IOTs: https://www.oecd.org/en/data/datasets/input-output-tables.html

[10] The homepage of Eora MRIO: https://www.worldmrio.com/

We also use China's national input-output tables from 2002 to 2020, available for 2002, 2005, 2007, 2010, 2012, 2015, 2017, 2018, and 2020. These tables are sourced from China's National Bureau of Statistics (NBS). In recent years (after 2017), the NBS has provided two versions of the input-output tables: the competitive and non-competitive. The competitive input-output table considers importing inputs substitutes for domestic inputs, whereas the non-competitive version separates sections for importing inputs. We rely on the national input-output tables to compute the upstream-weighted and downstream-weighted carbon pricing exposure for a specific sector at the sector-city-year level. Therefore, we use the competitive version to consider the substitution and complement effects of importing products.

3.3 Custom Data in China

We use detailed custom data of 2004, one year before the implementation of the EU ETS, to calculate the export (or import) weights of a specific industry from a Chinese city to a particular EU country within the total exports (or imports) of the city. The data source is the universe of Chinese transaction-level trade records, including detailed information on firm registration code, HS-8 product code, quantity and values of each trade transaction, and destination or original country. China's General Administration of Customs provides the data, and it is available with the firm's registration information, thus the city location, from 2000 to 2013. Using such information, we can generate the total exports and imports of the city-industry level each year from 2000 to 2013. Details of sector concordance can be found in the appendix.

We also get information on the city-level total exports and total imports from 2017 to 2020 from the China City Statistical Yearbook provided by NBS.

3.4 China's Environmental Outcomes

We collected data on the city-level emissions of several major pollutants from industrial processes in China from the City Statistical Yearbook spanning 2004 to 2020, provided by the NBS. This includes data on wastewater, sulfur dioxide (SO_2), nitrogen oxide (NO_x), and particulate matter (smoke and dust).

We have access to yearly average PM2.5 density estimates from the Tracking Air Pollution in China (TAP) platform [11] (Geng et al., 2021; Xiao et al., 2021). This platform

[11]The homepage of TAP: http://tapdata.org

provides a 10km x 10km level grid yearly average PM2.5 density measure. To aggregate the grid data into city-level information, we utilize the Chinese prefecture-level geo-map data from GADM [12].

We also use estimates of the county-level CO_2 emission inventory in China from 1997 to 2017 to measure the city-level carbon emission during this period. The data is from the Carbon Emission Accounts and Datasets(CEADs) platform [13] (Chen et al., 2020).

3.5 Environmental Regulation Stringency Index

To gauge the strictness of environmental regulations at the city level, we also use the text-based index of environmental regulation stringency (ESI), originally proposed by Chen et al. (2018) and used by Du and Li (2024) in a similar context. In the political landscape of China, the government's annual work report plays a crucial role at the national, provincial, and city levels as one of the most significant official documents. It serves the dual purpose of summarizing accomplishments from the past year and outlining plans for the year ahead. Each year, these annual work reports are viewed as strong indicators of the government's policy priorities and are expected to be achieved (Chen et al., 2018). Moreover, another reason the text-based stringency index, generated using city-level government work reports, is particularly suitable for our study is that local officials typically have significant discretion in devising the plan. Implementing the plans announced in each year's annual report is crucial in their promotion evaluation.

The city-level environmental regulation stringency index is calculated by dividing the length of sentences containing environment-related words by the total length of the full work report each year. We choose 14 environment-related words, which include PM2.5, PM10, SO_2, CO_2, COD, pollution, emission, emission reduction, air, low carbon, protect the environment, environmental protection, smog, and energy consumption intensity.

3.6 Environmental Penalty in China

To directly measure the stringency of environmental regulation at the city level, we use official records of environmental administrative penalties. We have access to a novel dataset containing the universe of detailed information on each environmental penalty from 2001 to 2020, including the date, city location, penalty type, fine amount, and firm sector. The

[12] The homepage of GADM: https://gadm.org/about.html

[13] The homepage of CEADs: https://www.ceads.net/

penalties encompass fines, license revocations, orders to rectify or suspend operations, sealing, seizures, professional restrictions, confiscation of property or illegal gains, administrative detention, and criminal arrests.

We focus on this detailed penalty data because, unlike pollution fees, taxes, or emission standards—which are often determined at higher administrative levels—city-level administrations primarily determine the frequency and severity of environmental penalties. As such, they provide a good proxy for gauging the stringency of environmental regulations at the city level.

3.7 Summary Statistics and Descriptive Evidence

Summary Statistics Table 1 presents summary statistics of the main indicators and outcomes used in this paper, divided into sector-city-level variables and city-level variables.

Panel A of Table 1 displays the summary statistics for the main city-sector-level outcomes and measures of sectoral exposure. On average, each sector received 28.87 environmental penalties per year, with total fines amounting to 89.3 thousand CNY (approximately 13,686 USD at the average exchange rate from 2000 to 2020). Among all sectors that received at least one penalty during the year, 63% are tradable sectors, namely agriculture, manufacturing, and mining.

Regarding carbon price exposure, the average sector has an export-weighted exposure of 0.66 million euros and an import-weighted exposure of 2.28 million euros to EU carbon costs. The export-weighted exposure to carbon cost rates averages 15,155.75 euros, while the import-weighted exposure averages 30,669.56 euros.

In terms of trade, the average sectoral total export value is 245.86 million USD, with an average export volume of 210.34 units and an average unit price of 3,215.86 USD. Conversely, the average sectoral import values, volumes, and unit prices are 188.15 million USD, 285.73 units, and 6,357.03 USD, respectively.

Panel B of Table 1 presents summary statistics for city-level variables. The average Environmental Regulation Stringency Index (ESI) is 0.06, indicating that, on average, 6% of the sentences in yearly government work reports are related to environmental topics. The city-level average export-weighted exposure to EU carbon costs is 1.40 million euros, and the import-weighted exposure is 1.14 million euros. The average city-level export-weighted exposure to carbon cost rates is 49,676.72 euros per million, while the import-weighted exposure is 79,045.74 euros per million.

Our measures of environmental outcomes are all at the city level. The average estimated total carbon emissions are 21.98 million tons of CO_2. On average, cities discharge 69.12 million tons of wastewater, 136.1 thousand tons of SO_2, 49.3 thousand tons of NOx, and 29.4 thousand tons of industrial particulates annually. During this period, the average annual PM2.5 concentration is 46.55 μg/m^3 (micrograms per cubic meter).

Descriptive Evidence Figure 2 illustrates time trends of average economic and environmental outcomes among Chinese cities. Panel (a) shows the steady and substantial increase in GDP per capita over time. Panels (c), (d), and (e) display similar patterns for pollution measures such as NO_x emissions, wastewater discharge, and annual average PM2.5 levels, all of which increased rapidly after China joined the World Trade Organization in 2001, remained at high levels until around 2013, and then declined as the central government emphasized environmental outcomes. China's national campaigns against pollution were effective in reducing major pollutants and PM2.5 levels, as evidenced by the sharp drops observed after 2013.

An exception is city-level carbon emissions, shown in panel (b) of Figure 2. Total carbon emissions continued to grow even after 2013 until around 2017. This is because carbon emissions were not included in national or local environmental goals during that period, and efforts were primarily focused on mitigating major pollutants.

Figure 3 illustrates the surge in environmental penalties, both in terms of the number of events and the total amount of penalties, as well as the regional distribution of penalties in China from 2000 to 2020. The number and total amount of environmental penalties were very low before 2010, began to increase in 2012, and remained moderate until 2015. Starting in 2016, both the number and amount of penalties dramatically increased, peaking in 2018. After 2018, there was a slight decline, but penalties remained at high levels. The regional distribution shown in Figure 3 indicates that penalties are concentrated in the eastern coastal areas, particularly in the major economic zones surrounding Beijing, Shanghai, and Guangzhou/Shenzhen.

4 Empirical Strategy

We begin by calculating the embodied carbon price burden of specific sectors in the EU, accounting for both direct costs of purchasing emission allowances to account for fuel combustion carbon emissions and indirect costs transmitted through upstream sectors.

We then construct a shift-share (Bartik-like) measure of carbon price exposure for Chinese cities at the city-sector-year level, using fixed pre-EU ETS export (or import) proportions as weights. Finally, we employ regression models to causally identify the impact of changes in carbon price exposure on trade, local environmental outcomes, and, crucially, the stringency of local environmental regulations in China.

4.1 Measuring Sectoral Embodied Carbon Price in Europe

Under the EU ETS, regulated firms must monitor and surrender sufficient emission allowances to cover their direct greenhouse gas emissions, primarily from fuel combustion and certain industrial processes, such as cement production. This creates a direct carbon pricing cost, which is often passed downstream through supply chains. Due to the interconnectedness of industries, an increase in carbon pricing in one sector affects downstream sectors and even other countries, especially within the EU. Even relatively cleaner industries bear indirect carbon costs from their upstream suppliers. To capture the total carbon impact of a product or industry—including both direct and indirect emissions—we adopt a life-cycle or carbon footprint approach.

Following Shapiro (2021) and Wang (2024), we consider a global economy with N countries, each divided into S sectors. Let A be the $NS \times NS$ input-output matrix, where each column represents the inputs required by an industry from all other industries, both domestically and abroad, and each row represents the outputs supplied by an industry. Let x be the $NS \times 1$ vector of total outputs, and d be the $NS \times 1$ vector of final demands. The accounting identity $x = Ax + d$ holds, indicating that total output equals intermediate inputs plus final demand. This can be rearranged to $x = (I - A)^{-1}d$, where $(I - A)^{-1}$ is the Leontief inverse matrix, capturing the total input requirements—including all direct and indirect inputs—to produce a unit of final demand.

Using this framework, we express the embodied carbon price burden for sector k in country j at time t as:

$$g_{jk,t} = \sum_{i,s} l_{ijsk,t} E_{is,t} \tau_{is,t}, \tag{1}$$

where $g_{jk,t}$ is the embodied carbon price burden for sector k in country j at time t. The term $l_{ijsk,t}$ is an element of the Leontief inverse matrix $(I - A)^{-1}$, representing the monetary amount of inputs from sector s in country i required to produce one monetary unit of output in sector k in country j. The variable $E_{is,t}$ denotes the direct carbon emission intensity of sector s in country i at time t, that is, the direct emissions per unit of output. Alternatively, we also use an alternative definition of $E_{is,t}$ as the total direct carbon emission of sector s in country i at time t. $\tau_{is,t}$ is the carbon price applicable to sector s in country i at time t, determined by sectoral coverage and the average yearly price of EU ETS allowances.

This formulation assumes perfect competition and complete pass-through of carbon costs along the supply chain, meaning that additional carbon costs are proportionally transmitted to downstream sectors. All monetary values in the input-output tables and related datasets are converted to 2015 Euros for standardization purposes.

4.2 Measuring City-Sector Carbon Pricing Exposure in China

To measure the exposure of Chinese cities to EU ETS carbon prices, we construct a weighted average of the EU carbon price burdens at the country-sector level, using fixed pre-EU ETS export shares as weights. Using contemporary trade proportions could introduce bias due to unobserved economic factors and concurrent domestic policies affecting trade and environmental outcomes. Therefore, following the shift-share methodology commonly used in the international trade literature (Kovak, 2013; Hakobyan and McLaren, 2016; Dix-Carneiro and Kovak, 2015, 2017, 2019; Dai et al., 2021, 2020), we use export (or import) shares from the year before the EU ETS implementation.

Specifically, we define the carbon pricing exposure for city c at time t as:

$$\text{Exposure}_{ct} = \sum_{j,k} g_{jk,t} R_{cjk,2004}, \tag{2}$$

and the sectoral exposure for city c, sector k, at time t as:

$$\text{Exposure}_{ckt} = \sum_{j} g_{jk,t} R_{cjk,2004}. \tag{3}$$

Here, Exposure_{ct} is the overall carbon pricing exposure of city c in year t, and Exposure_{ckt} is the exposure for sector k in the city c in year t. The term $g_{jk,t}$ is the embodied carbon price burden for sector k in EU country j at time t, as defined in equation (1). The weights $R_{cjk,2004}$ are the ratios of exports from city c, sector k, to EU country j in 2004, relative to total exports. We also test alternative weighting schemes, such as using average export shares from 2002 to 2004 or expressing weights as ratios to total GDP in 2004, as robustness checks.

Figure 4 displays the time trends of the average export- and import-weighted carbon price exposures among Chinese cities from 2000 to 2020. Both the import- and export-weighted exposures to EU carbon costs or carbon cost rates follow similar time trends to the trajectory of carbon prices in the EU, as shown in Figure 3. However, the variations are mostly across cities or different sectors within the same cities. Figure 5 illustrates the regional variation of carbon price exposure at the city level. We observe that the four measures of carbon price exposure exhibit significant regional variations. Moreover, the regional distributions of export- and import-weighted carbon price exposures do not coincide, implying that they capture different city or sectoral attributes affecting import and export structures. Additionally, the regional variations of carbon price exposure are widely dispersed and not concentrated solely in coastal areas. These dispersions support our identification strategy, as they suggest that the shift-share carbon price exposure measures can be considered exogenous shocks.

4.3 Regression Model

To identify the causal effect of changes in EU carbon pricing exposure on Chinese cities, we estimate the following regression models:

$$\ln(Y_{ct}) = \beta \ln(\text{Exposure}_{ct}) + \Gamma X_{ct} + \delta_t + \sigma_c + \epsilon_{ct}, \tag{4}$$

$$\ln(Y_{ckt}) = \beta \ln(\text{Exposure}_{ckt}) + \Gamma Xckt + \delta_t + \sigma_c + \epsilon_{ckt}. \tag{5}$$

Here, $\ln(Y_{ct})$ denotes the logarithm of city-level outcomes for city c at time t, such as total exports, imports, trade volume, environmental indicators (e.g., pollutant emissions, carbon emissions, average PM2.5 levels), environmental regulation stringency indices, and environmental penalties. Similarly, $\ln(Yckt)$ represents the logarithm of sector-level outcomes for sector k in the city c at time t, such as city-sector exports, imports, and environmental regulatory events.

The main explanatory variables, $\ln(\text{Exposure}_{ct})$ and $\ln(\text{Exposure}_{ckt})$, are the logarithms of the carbon pricing exposure measures defined earlier. The coefficient β captures the elasticity of the outcome variable with respect to carbon price exposure.

X_{ct} and X_{ckt} are vectors of control variables at the city and city-sector levels, respectively. The terms σ_c and δ_t represent city fixed effects and year fixed effects, controlling for time-invariant city characteristics and common temporal shocks. In city-sector specifications, we include city-year and sector-year fixed effects. The error terms ϵ_{ct} and ϵ_{ckt} are clustered at the city or city-sector level.

4.4 Identification Assumptions and Threats to Identification

First introduced by Bartik (1991) and formalized by Blanchard and Katz (1992), the shift-share (or Bartik) method has been widely used to identify the effects of common shocks across different units. Recent methodological work has explored the validity of shift-share instruments as two-stage least squares (TSLS) estimators, examining their consistency and identification assumptions (Adão et al., 2019; Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020); see also Borusyak et al. (2024) for a review. These studies have established the equivalence between using shares or shocks as instruments and have highlighted key identification conditions, the relevance condition, and exogeneity condition.

The relevance assumption requires that the weights (shares) have predictive power for the current exposure to shocks. The exogeneity assumption, analogous to the exclusion restriction in TSLS, requires that the shares are exogenous to the error terms after controlling for covariates and fixed effects. Importantly, even if the shares are not exogenous, consistent estimates can be obtained if the shocks are independent and exogenous (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Even though the validity of identification and estimation consistency is often illustrated in an instrumental variable setting in recent methodological literature (Goldsmith-Pinkham et al., 2020; Adão et al., 2019; Borusyak et al., 2022), the exclusion restriction remains the same when shift-share measures are used in reduced-form specifications (Goldsmith-Pinkham et al., 2020).

In our context, we construct the carbon pricing exposure of Chinese cities using predetermined export (or import) shares and exogenous variations in EU carbon pricing. The exogeneity of the EU country-sector-level carbon price burdens stems from EU policy changes and global economic conditions, which are plausibly independent of contemporaneous outcomes in Chinese cities. The pre-EU ETS export shares from 2004 are unlikely to be correlated with later changes in city-level outcomes, especially given significant shifts in China's environmental policies after 2013. As Goldsmith-Pinkham et al. (2020) note, identification is strengthened when the research design resembles a difference-in-differences framework with pre-treatment periods; we utilize data from 2001 to 2004 as such pre-periods.

To further mitigate endogeneity concerns, we incorporate two novel measures of EU carbon pricing changes proposed by Känzig (2023): the *carbon policy surprise* and the *carbon policy shock*. The carbon policy surprise captures high-frequency fluctuations in EUA futures prices around regulatory events, relative to wholesale electricity prices, effectively isolating policy-induced price changes from broader economic influences. The carbon policy shock, derived using an external instruments VAR model with the surprise series as an instrument, further addresses potential reverse causality.[14] We re-estimate our main regressions using these alternative measures and find consistent results (see Section 5.5 and Appendix C for details).

Additional Identification Threats While our identification strategy relies on the exogeneity of EU carbon pricing shocks and pre-determined export shares, potential threats remain. One concern is that unobserved factors influencing the initial export shares and subsequent outcomes could bias our estimates. For instance, cities with higher initial exposure might differ systematically in ways that affect environmental regulation independently of EU carbon pricing. To address this, we include city and year fixed effects and, in different specifications, city-year and sector-year fixed effects to control for time-invariant or time-variant city-specific unobserved heterogeneity and common temporal shocks.

Another concern is that changes in China's domestic national environmental policies or global economic conditions might differentially affect cities based on their initial export composition. We mitigate this by conducting robustness checks using alternative weighting schemes, such as using average export shares from 2002 to 2004 or expressing weights relative to total GDP. Additionally, we control for city-level economic variables that could influence environmental regulation stringency, including GDP per capita and registered population.

Measurement error in the constructed exposure variables could also attenuate our estimates. We believe this is less of a concern for our study design because the carbon cost sectoral coverage and average price are from official documents, and the trade ratios in 2004 are calculated using the universe of China's customs data. We also perform sensitivity analyses to assess the robustness of our results to alternative measures of carbon prices in the EU.

[14] Data available at `https://github.com/dkaenzig/carbonpolicyshocks`; we thank Diego Känzig for providing these data.

5 Results

We begin by examining the relationship between Chinese city-sector exposure to EU carbon prices and environmental penalties in China. We then analyze the impact of carbon price exposure on city-sector exports, total carbon emissions, and pollution levels. Our findings indicate that stricter carbon policies in the EU have spillover effects on China's production patterns, influencing both environmental outcomes and the stringency of local environmental regulations.

5.1 Impacts of Carbon Price Exposure on Environmental Regulation in China

We first assess the causal impact of EU carbon price exposure on the stringency of environmental regulations across different sectors in Chinese cities. Table 2 presents regression results based on Equation (5), utilizing city-sector-level environmental penalty data. The results show that higher exposure to EU carbon prices, measured by export ratios, is associated with an increase in environmental regulatory actions. Specifically, a 100% increase in EU carbon price exposure leads to a 1% increase in the number of environmental penalties within the affected sectors and a 0.7% increase in the total monetary amount of penalties.

In contrast, when exposure is measured using import ratios, we find no significant impact on city-sector-level penalties. In fact, there is some suggestive evidence that higher import-weighted carbon price exposure may lead to less stringent environmental regulation.

Additionally, we present regression results using the environmental regulation stringency index at the city level. These results indicate that higher export-weighted exposure to EU carbon prices is associated with increased overall stringency in environmental regulation across cities, although the effects are statistically insignificant. Conversely, no significant impacts are detected when exposure is measured using import ratios.

We also consider an alternative specification of carbon price exposure, defined as the weighted average of EU carbon price rates—measured by the cost of carbon emissions per unit of monetary output. The regression results using this measure, shown in columns (3) and (4) of Table 2, are consistent with our main findings and of similar magnitude.

Overall, our findings suggest that stricter carbon policies in Europe lead to more stringent environmental regulation in China, the world's largest carbon emitter. These ripple effects may appear counterintuitive, given prevalent concerns about carbon leakage. However, we argue that this apparent policy coordination is actually a passive adjustment induced by production shifts and carbon leakage—a mechanism that we explore in the subsequent regression results.

5.2 Impacts of Carbon Price Exposure on International Trade in China

We examine the impact of carbon price exposure on city-sector-specific total exports and imports. Table 3 indicates that higher export-weighted exposure to EU carbon prices among city-sector pairs leads to increased total exports of the specific sector from the city. Specifically, a 100% increase in carbon price exposure leads to a 6.2% rise in the total export value of that sector from the city. Similarly, a 100% increase in import-weighted carbon price exposure leads to a 6.9% increase in the total import value of that sector to the city.

When we decompose the total export and import values into quantities and unit prices, columns (3) and (5) in Table 3 show that the increase in total export values arises solely from higher quantities, with no significant changes in unit prices. This suggests that when EU competitors face higher carbon costs, Chinese exporting firms gain a competitive advantage and choose to export more within the same sector to both Europe and the rest of the world while maintaining stable unit prices. This result provides clear evidence of production shifts due to stricter carbon policies in the EU, and we find no evidence that higher carbon costs in the EU have any pass-through effects on the prices of Chinese competitors' products.

Furthermore, columns (9) and (11) in Table 3 show that the increase in total imports in sectors with higher import-weighted carbon price exposure is driven by both higher import quantities and higher unit prices. The rise in unit prices is naturally due to the higher carbon costs of products from the EU. The increase in quantities may reflect substitution towards imports from other countries as Chinese firms seek alternative suppliers due to higher EU prices.

We also present regression results using the carbon cost rate exposure, and the findings are very similar in sign and magnitude.

5.3 Impacts of Carbon Price Exposure on Environmental Outcomes in China

We now explore the causal relationship between exposure to EU carbon prices and environmental outcomes in Chinese cities from 2005 to 2020. The first two columns in Table 4 show that higher export-weighted carbon price exposure leads to slightly higher total city-level carbon emissions and wastewater pollution, although the effects are statistically insignificant. This positive relationship aligns with the standard carbon leakage narrative: higher carbon prices in the EU raise firms' costs and lead to a shift in production to countries with lower carbon prices, offsetting emissions reductions in Europe.

In contrast, we find significant negative impacts of higher import-weighted carbon price exposure on total carbon emissions and wastewater emissions. These findings suggest that stricter EU carbon policies lead to reduced environmental pollution in China through the import channel. Higher carbon costs make imported intermediates and final goods from the EU more expensive. While the increase in unit prices reflects higher carbon costs, the increase in import quantities may be driven by substitution towards imports from other countries. Reduced reliance on EU inputs may hinder the production of downstream firms that cannot easily find alternative suppliers, leading to decreased manufacturing activity and lower emissions.

The last two columns of Table 4 show a similar pattern for PM2.5 levels: higher export-weighted carbon price exposure causally induces higher annual average PM2.5 concentrations, whereas higher import-weighted carbon price exposure leads to lower $PM_{2.5}$ levels.

Columns (5) and (6) in Table 4 present the impacts on NO_2 emissions, a major pollutant in China due to extensive coal combustion. Higher import-weighted carbon price exposure leads to lower NO_2 emissions, consistent with reduced manufacturing activity. Interestingly, higher export-weighted carbon price exposure is also associated with lower NO_2 emissions, which is inconsistent with the carbon leakage hypothesis that predicts increased emissions due to production shifts. One potential explanation for this negative association is that higher exposure to EU carbon prices prompts stricter local environmental regulation, particularly targeting pollutants like NO_2, which have been a primary environmental concern for local officials.

5.4 Dynamic Impacts of Carbon Price Exposure

We also explore the dynamic impacts of both export and import-weighted exposure to total carbon costs and carbon cost rates in the EU on environmental regulations, total trade, and environmental outcomes, using the local projection impulse response functions method proposed by Jordà (2005). Specifically, we estimate the following regression models:

$$\ln(Y_{c,t+h}) = \beta \ln(\text{Exposure}_{ct}) + \Gamma X_{c,t+h} + \delta_{t+h} + \sigma_c + \epsilon_{c,t+h}, \tag{6}$$

$$\ln(Y_{ck,t+h}) = \beta \ln(\text{Exposure}_{ckt}) + \Gamma X_{ck,t+h} + \delta_{t+h} + \sigma_c + \epsilon_{ck,t+h}. \tag{7}$$

Figure B.1 shows the dynamic impacts of carbon price exposure on Chinese local environmental penalties. The figures demonstrate that increases in environmental penalty numbers and sums respond quickly to higher export-weighted exposure to EU carbon prices. Meanwhile, there are persistent positive impacts of export-weighted exposure to EU carbon costs and opposite impacts of import-weighted exposure on the Environmental Regulation Stringency Index (ESI).

Similarly, the regression results shown in Figure B.2 indicate that total sectoral exports increase more in response to higher export-weighted exposure in the current year, driven solely by higher export volumes with no change in unit prices. There are also persistent impacts of higher export-weighted EU carbon costs on sectoral export values and volumes, though the magnitudes are smaller. Subfigures (e) and (f) in Figure B.2 show no changes in unit prices even after several years, suggesting limited pass-through to the unit prices of Chinese exports. In contrast, Figure B.3 displays the dynamic regression results on total import values, volumes, and unit prices. There are similarly strong and immediate increases in import total values, volumes, and unit prices, driven by higher import-weighted exposure to EU carbon prices.

Figure B.4 and Figure B.5 illustrate the regression results using Equation (6) on environmental outcomes. Figure B.4 shows that higher export-weighted carbon price exposure leads to small and non-persistent rises in total city carbon emissions and wastewater discharges. There is also evidence of decreases in NOx, SO2, and industrial particulate discharges, although these are statistically insignificant, implying that higher environmental pressure incentivizes rapid policy responses, offsetting increases in pollution. However, subfigures (a) and (b) in Figure B.5 and subfigures (e) and (f) in Figure B.5 both show evidence of strong and immediate increases in carbon emissions and average PM2.5 levels.

Conversely, higher import-weighted carbon price exposure causes large, immediate, and persistent decreases in all environmental outcomes, including carbon emissions, major pollutants, and PM2.5 levels.

In summary, the findings using Equation (7) and Equation (6) clearly show that higher export-weighted carbon price exposures lead to quick responses among Chinese local officials through stricter environmental regulations, driven by immediate increases in total exports and heightened environmental pressures. On the other hand, higher import-weighted exposure to EU carbon prices causes a small and insignificant drop in regulation stringency due to quick increases in import unit prices and persistent declines in pollution.

5.5 Robustness Checks

In this subsection, we validate our regression results on the positive relationship between higher carbon prices in the EU and stricter environmental regulations in China using several robustness checks. We show regression results using different regression model specifications, including the one incorporating different fixed effects, the one using lagged values of carbon price exposure, and the one using different weights within the shift-share measures. Additionally, we incorporate two alternative novel measures of EU carbon pricing changes proposed by Känzig (2023): the *carbon policy surprise* and the *carbon policy shock*, to validate the robustness of our identification strategy.

Different Fixed Effects We validate our results by incorporating different fixed effects. C.1 and Table C.2 contain the regression results of carbon price exposure on sector-specific penalties and trade outcomes, including time fixed effects, sector fixed effects, and year fixed effects, as well as the results including city-year fixed effects and sector fixed effects. The results remain consistent in both signs and magnitudes, except for the impacts of import-weighted carbon price exposure on import volumes, which are no longer significant. In this case, all increases in import values stem from higher unit prices. This finding strengthens our narrative, as it suggests that it was difficult to substitute intermediate product imports from the EU with products from other countries, thereby hindering local firms that depend on EU inputs and leading to strategically more lenient regulation by local officials.

Using Lagged Carbon Price Exposure To account for price rigidity in international trade and allow for potential adjustments in trade patterns and supply networks, we explore the causal impacts of lagged values of carbon price exposure on environmental penalties, trade outcomes, and pollution outcomes. Table C.3 shows consistent estimation results in signs and magnitudes, with even more significant negative impacts of the import-weighted carbon exposure on the number of penalties. Table C.4 also shows consistent results regarding impacts on trade values, volumes, and unit prices, as well as similar estimation results in Table C.5 for pollution outcomes. Moreover, to further account for this concern, we also conduct regressions using the three-year moving averages (averages of the current, the one-year lagged, and the two-year lagged values) of the exposures to carbon prices in the EU as explanatory variables. Table C.6, Table C.7, and Table C.8 show the regression results on environmental penalties, total trade, and environmental outcomes, and all the main coefficients estimates are consistent with the main specification.

Using Different Weights in Carbon Price Exposure

Using Different Measures of Carbon Price To further address concerns of endogeneity bias, we validate our main regression results using alternative measures of sectoral carbon prices in the EU. We replace the yearly average EU ETS price with the *carbon policy surprise* and the *carbon policy shock* from Känzig (2023), which capture price changes within very short intervals following major regulatory events.

6 Mechanisms

In this section, we explore the mechanisms underlying our primary findings on the ripple effects of stricter carbon policies in the EU on environmental regulations in China. We provide further evidence demonstrating that the main channel of this non-cooperative environmental policy coordination is production and carbon leakage. However, the direction of these spillover effects may differ between exporting sectors and firms that rely heavily on EU inputs, leading to contrasting strategic policy responses by China's local officials.

6.1 Trade-off Between Economic Performance and Environmental Protection

As described in Section 2, local officials in China face trade-offs between economic performance and environmental outcomes, with environmental standards increasingly weighted in promotion evaluations. Regression results in Table 3 indicate that industries with higher export-weighted exposure to the EU carbon price are exporting more in total. The increase in exports can happen both to the EU and the rest of the world due to the comparative advantage of Chinese products within these sectors. Furthermore, Table 4 shows that the export surge leads to higher carbon emissions, increased wastewater discharge, and elevated average annual $PM_{2.5}$ levels at the city level. This rise in sectoral production and exports is a primary reason why higher carbon prices in the EU result in increased emissions and pollution in China, providing evidence of carbon leakage.

Facing the spillover effects of stricter carbon policies in the EU on both sectoral exports and pollution, local officials have an incentive to raise environmental regulation stringency, increase inspections, and issue more penalties to control pollution and meet environmental standards in their evaluations.

These passive policy responses can be either targeted, where only firms benefiting from higher carbon costs for their EU counterparts are more stringently regulated, or applied on a city-wide scale, allowing officials more policy space to enforce stricter regulations while maintaining sufficient economic output.

In contrast, Table 3 also shows that sectors depending more on imports from the EU import higher values when carbon prices rise, partly due to increased unit import prices. Moreover, Table 4 provides consistent evidence that cities more exposed to imports from the EU have lower annual emissions of major pollutants. The lower emissions imply that cities with firms heavily reliant on EU inputs experience negative spillover effects due to higher intermediate costs. Consequently, more relaxed environmental regulation for sectors with higher import-weighted carbon price exposure may also be a passive policy response by local officials to support affected firms or a mechanical reaction to lower pollution.

We provide further evidence to determine whether the policy response by Chinese local officials is targeted or city-wide. Table 5 and Table 6 display the impacts of carbon price exposure on sectoral environmental regulation separately for tradable and non-tradable sectors.[15] Table 5 presents regression results for tradable sectors, showing larger impacts on the number of penalty events and the total sum of penalties compared to the impacts on all sectors. However, Table 6 indicates that, with one exception, there are no significant differences in penalty events or the sum of penalties issued in cities with higher versus lower exposure to the export-weighted carbon price. This suggests that in cities facing increased pollution due to export booms, the intensification of environmental regulation does not affect non-tradable sectors.

Interestingly, Table 6 also shows that in cities experiencing negative shocks from increased costs of EU-imported inputs, there are more penalties against non-tradable sectors. One explanation is that local officials issue fewer penalties to affected tradable sectors while raising regulatory standards for non-tradable sectors to balance overall environmental outcomes. These analyses imply that the stringent environmental regulation responding to the spillover effects of higher EU carbon prices is more likely targeted at sectors with higher emissions and pollution. Simultaneously, there is evidence that local officials strategically adjust environmental regulations to control the overall pollution level.

6.2 Alternative Explanations

Beyond the mechanism illustrated above, whereby Chinese officials balance economic and environmental outcomes with targeted passive policy responses, other possible explanations exist for why stricter carbon policies in the EU are associated with higher environmental regulation stringency in China. We discuss these possibilities and demonstrate that none of them could convincingly explain our main findings.

National Policy Shifts in China One alternative explanation is that the stricter regulation in China results from a nationwide policy shift due to heightened concerns about environmental outcomes or international agreements. However, our identification strategy and the variations in carbon price exposure rule out this possibility. By utilizing variation at the city, sector, and year levels and controlling for both city-year and sector-year fixed effects, we effectively exclude common national policy shocks and time trends at both the sector and city levels.

[15] Following Dai et al. (2020, 2021), we define tradable sectors as agriculture, manufacturing, and mining.

Industrial Policies Another potential explanation is that stricter environmental regulations are due to local industrial policies that increase production and pollution. For this to account for our findings, these local industrial policies would need to correlate with city export ratios to EU countries in 2004. Even if this were the case, it would not rule out the causality between EU carbon prices and environmental regulation in China, as the causality could also come from the orthogonality between sectoral embodied carbon price changes in the EU and outcomes in China.

Carbon Policies in Other Countries It is also possible that the observed policy responses are reactions to carbon policy changes in other countries, such as the United States. However, this explanation would require that the export ratios to all EU countries in 2004 proportionally reflect export ratios to the U.S. and that carbon policy changes in the U.S. match those in the EU regarding sectoral embodied carbon price changes. These conditions are unlikely to hold, making this explanation implausible.

7 Discussion and Conclusion

A major concern of unilateral carbon policy is carbon leakage, and to mitigate the impacts of production and carbon emission leakage, there have been large amounts of both theoretical and policy debates and practices. This paper contributes to this debate by showing that carbon policies in one major region did bring production and carbon emissions to foreign countries. However, it could also lead to a passive policy response of foreign countries as long as environmental outcome is also their policy object there. Specifically, we show the causal impacts of increasing carbon prices within the EU ETS regime on environmental regulations in China through the channel of exports and carbon emission shifts to China, using a novel dataset containing the universe of Chinese local environmental penalties. To generate a causal relationship, we employ a shift-share measure of the exposure to EU carbon prices at city-sector levels in China, using fixed pre-EU ETS EU trade ratios and common varying embodied carbon costs within the EU, including both direct and indirect carbon cost through supply chains.

Our results show that higher exposure to the export-weighted EU carbon prices leads to higher environmental penalties in amount and sum of values. In comparison, higher import-weighted exposure to carbon prices causes slightly fewer environmental penalties. We provide further evidence that the stricter regulations are a result of increasing total exports, total production, and pollution. In contrast, the slightly more lenient regulations come from higher unit prices of EU-imported intermediates and lower environmental content. We also show that the stricter environmental regulations are targeted against tradable sectors and not a city-wide policy change. However, the local officials switched policies strategically by raising penalties against non-tradable sectors while relaxing regulation on reversely affected tradable firms.

To the best of our knowledge, this is one of the first papers empirically showing the spillover effects of carbon policies in one economy on the environmental policy responses of another country. We also contribute to the theoretical literature by showing the potential extension of dynamic global carbon policy interactions.

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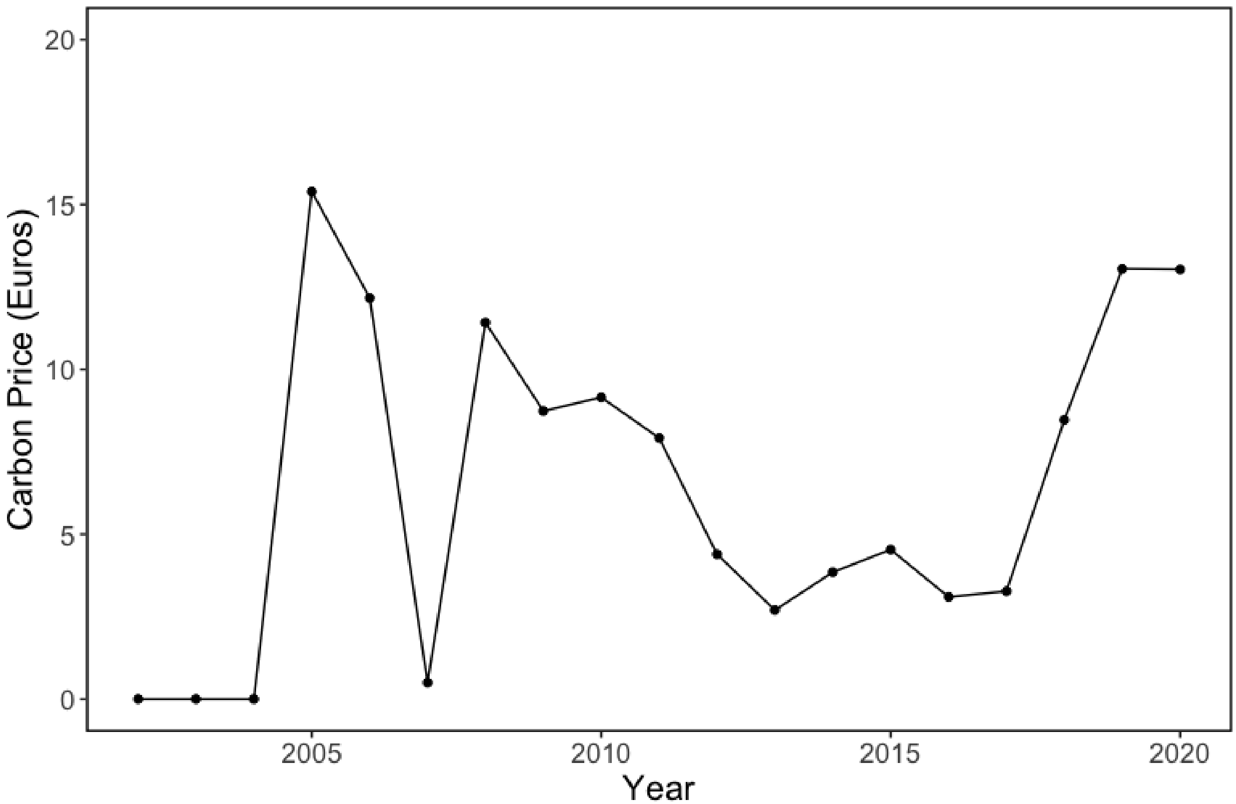
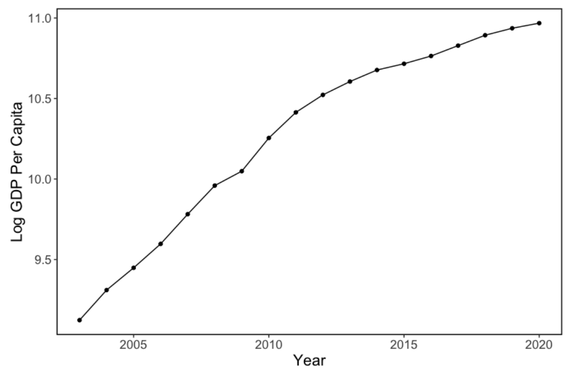
Figures

Figure 1: Carbon Prices in Europe

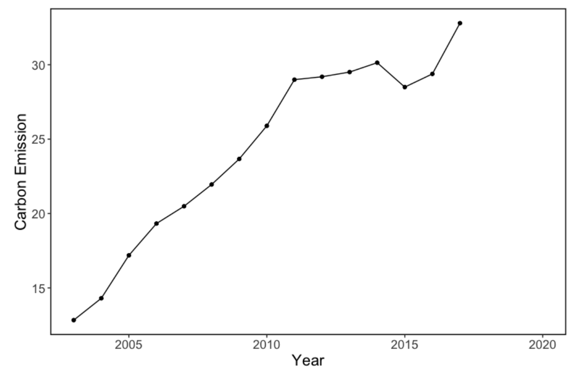


Note: This figure shows the EU ETS carbon emissions allowance price from 2000 to 2020. The time trend of the carbon permit prices in the EU shows significant timing variation as a result of both stricter carbon policies and changing supply and demand. The source of the carbon price is the World Carbon Pricing Database managed by RFF.

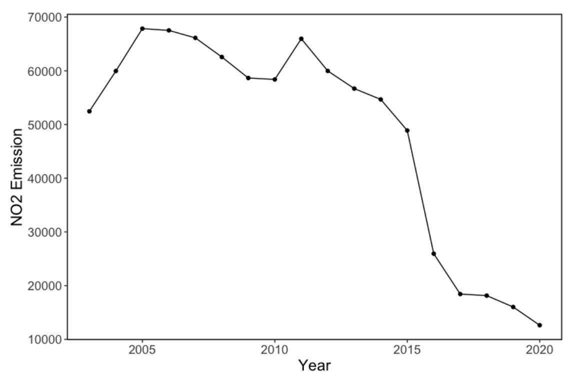
Figure 2: Economic and Pollution Trends in Chinese Cities



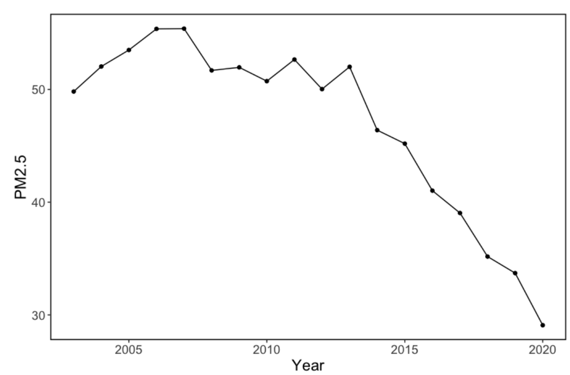
(a) Log GDP Per Capita



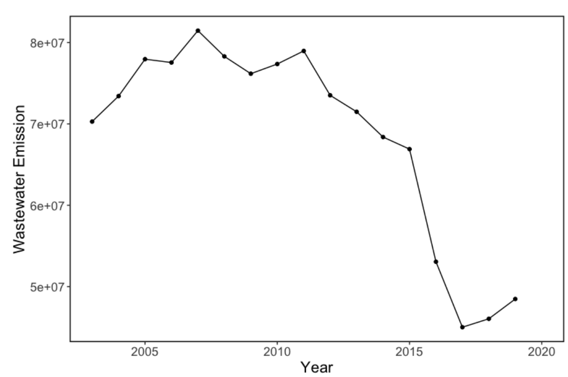
(b) Carbon Emission



(c) NO_x Emission



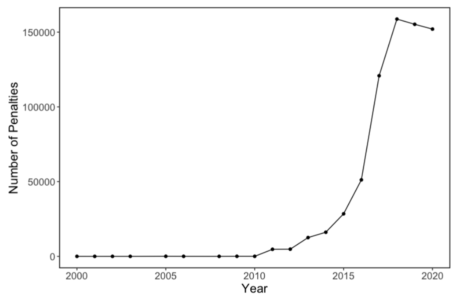
(d) $PM_{2.5}$



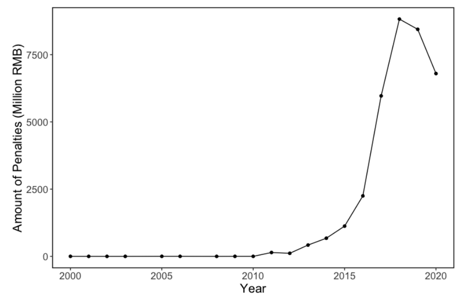
(e) Waste Water Emission

Note: This figure shows logged values of GDP per capita, carbon emissions, NO_x and wastewater discharges, and yearly average PM2.5 levels averaged by prefectures in China from 2000 to 2020. Sources of each outcome can be found in Section 3.

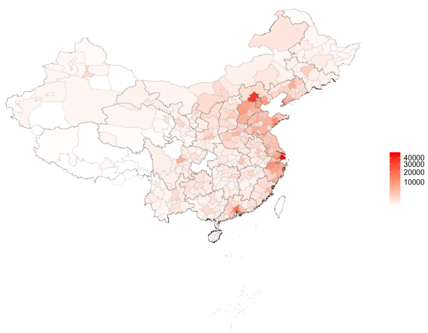
Figure 3: Environmental Penalties in Chinese Cities



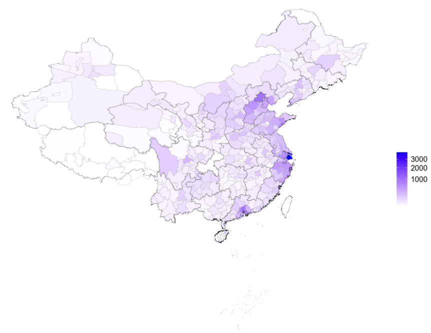
(a) Number of Penalties



(b) Amount of Penalties (Million RMB)



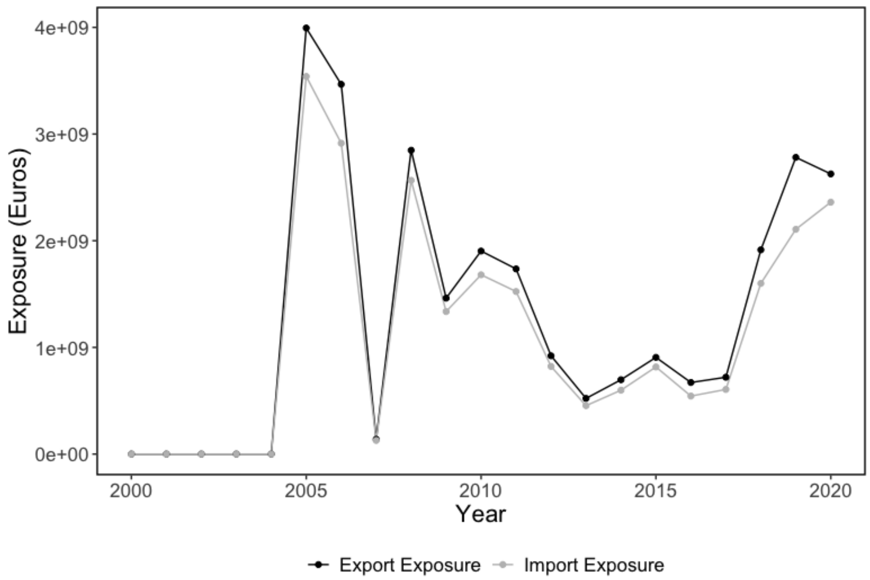
(c) Number of Penalties



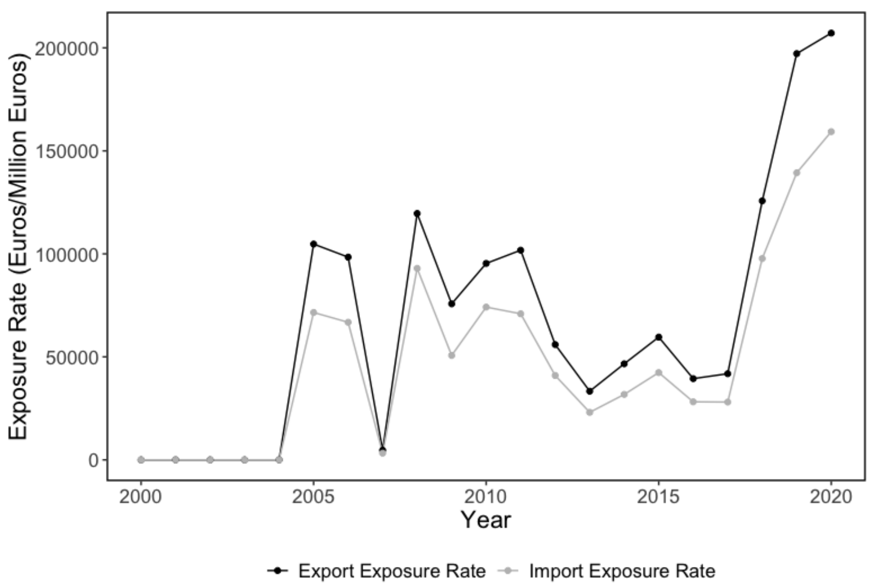
(d) Amount of Penalties (Million RMB)

Note: This figure shows the total number and sum of values of environmental penalties in China from 2000 to 2020, as well as the distribution of the total number and total values of penalties from 2000 to 2020. The time trends of environmental penalties show dramatic increases over time, especially after 2013. The geographic distributions of the total penalties show the dispersion of the penalties and show that most penalties were concentrated in east coastal regions. Sources of each outcome can be found in Section 3.

Figure 4: Carbon Exposure Trends in Chinese Cities



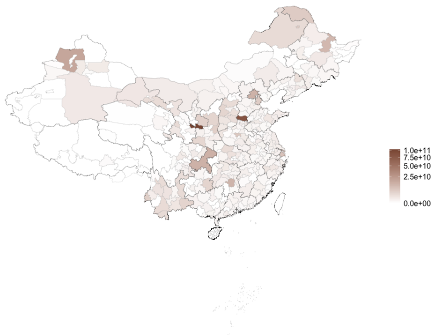
(a) Exposure (Euros)



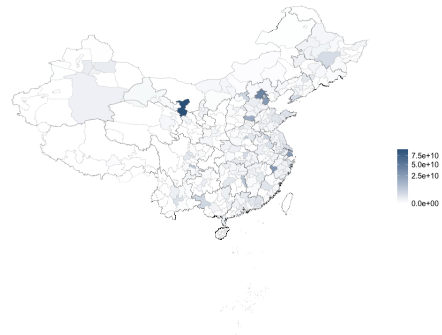
(b) Exposure Rate (Euros/Million Euros)

Note: These figures show the time trends of the shift-share measures of export and import-weighted exposures to carbon total cost and carbon cost rates at the city level in China from 2000 to 2020, calculating using Equation (2). They show a consistent trajectory with the change of the EU carbon price.

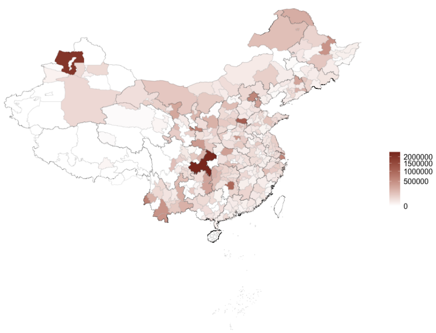
Figure 5: Maps of Carbon Exposure in Chinese Cities



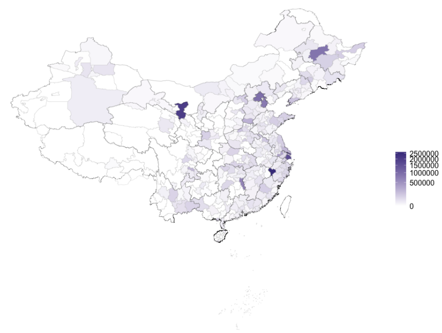
(a) Export Exposure (Euros)



(b) Import Exposure (Euros)



(c) Export Exposure Rate (Euros/Million Euros)



(d) Import Exposure Rate (Euros/Million Euros)

Note: These figures show the geographic distribution of the average measures of the shift-share measures of export and import-weighted exposures to carbon total cost and carbon cost rates at the city level in China from 2000 to 2020, calculating using Equation (2). It shows that the regional distributions of exposures to total carbon costs and carbon cost rates are similar, but the export and import-weighted carbon price exposure show very different geographic distribution patterns. Moreover, none of them coincide with the geographic distribution of total environmental penalties and the sum of environmental penalties, validating our identification strategy.

Tables

Table 1: Summary Statistics

	Summary Statistics		
Variable	**N**	**Mean**	**SD**
Panel A: Sector-Level Variables			
Number of Penalties	54,944	28.87	626.27
Total Penalties (in 10 Thousand CNY)	51,706	8.93	36.28
Tradable Sector	51,678	0.63	0.48
Sector Export Exposure (in million 2015 Euro)	54,944	0.66	28.07
Sector Import Exposure (in million 2015 Euro)	54,932	2.28	120.66
Export Exposure Rate (Euro/million 2015 Euro)	54,944	15,155.75	378,271.77
Import Exposure Rate (Euro/million 2015 Euro)	54,932	30,669.56	1,134,277.46
Total Sector Exports (in million USD)	77,614	245.86	2,331.63
Total Sector Export Amount (in million units)	77,614	210.34	2,216.81
Sector Export Price (USD per unit)	77,573	3,215.86	260,063.45
Total Sector Imports (in million USD)	77,614	188.15	2,036.65
Total Sector Import Amount (in million units)	77,614	285.73	3,100.00
Sector Import Price (USD per unit)	77,057	6,357.03	179,261.43
Panel B: City-Level Variables			
ESI	4,964	0.06	0.04
Export Exposure (in million 2015 Euro)	6,599	1.40	10.89
Import Exposure (in million 2015 Euro)	6,551	1.14	9.09
Import Exposure Rate (Euro/million 2015 Euro)	6,551	49,676.72	324,794.88
Export Exposure Rate (Euro/million 2015 Euro)	6,599	79,045.74	301,107.53
Carbon Emissions (in million tons)	5,533	0.00	0.00
Wastewater Emissions (in million tons)	4,504	69.12	88.40
SO_2 Emissions (in tons)	2,322	136,128.96	215,909.99
NO_x Emissions (in tons)	4,758	49,346.95	48,986.15
Particulate Emissions (in tons)	4,752	29,428.38	110,738.30
PM2.5 Concentration (μg/m^3)	6,515	46.55	22.23
Log GDP per Capita	4,675	10.24	0.84
Log Registered Population	4,972	5.85	0.70

Note: This table shows the summary statistics for the city-sectoral level and the city-level datasets. The city-sectoral level dataset contains sector information of 37 unique sectors from 338 prefectures from 2000 to 2020. The city-level dataset contains city information on 338 prefectures from 2000 to 2020.

Table 2: Carbon Price Exposure and Environmental Regulation in China

	Dependent variable:					
	Log(Penalty Number)	Log(Penalty Sum)	ESI	Log(Penalty Number)	Log(Penalty Sum)	ESI
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Exposure-Export)	0.010***	0.007***	0.0005			
	(0.003)	(0.002)	(0.0003)			
Log(Exposure-Import)	−0.003	−0.001	−0.0001			
	(0.002)	(0.002)	(0.0003)			
Log(Rate Exposure-Export)				0.013***	0.008***	0.0005
				(0.003)	(0.002)	(0.0004)
Log(Rate Exposure-Import)				0.002	−0.001	−0.0001
				(0.003)	(0.002)	(0.0003)
Year FE			Y			Y
City FE			Y			Y
Year-City FE	Y	Y		Y	Y	
Year-Sector FE	Y	Y		Y	Y	
Controls			Y			Y
Observations	28,973	26,448	4,598	28,973	26,448	4,598
R^2	0.623	0.387	0.485	0.623	0.387	0.485
Adjusted R^2	0.584	0.319	0.450	0.584	0.320	0.450

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1, 2, 4, and 5 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. Columns 3 and 6 report the estimates from regression Equation (4) for the logged values of the city-level environmental regulation stringency index (ESI). The independent variable is the city-level weighted sums of four exposures to the EU carbon prices. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions on city-level outcomes. Standard errors in parentheses are clustered at the city level.

Table 3: Carbon Price Exposure and Exports/Imports in China

	Dependent variable:											
	Log(Value)		Log(Volume) Export		Log(Prices)		Log(Value)		Log(Volume) Import		Log(Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Exposure-Export)	0.071***		0.070***		−0.0004		0.022***		0.023***		−0.003	
	(0.006)		(0.006)		(0.002)		(0.006)		(0.006)		(0.002)	
Log(Exposure-Import)	−0.020***		−0.023***		0.001		0.059***		0.048***		0.018***	
	(0.006)		(0.006)		(0.002)		(0.006)		(0.006)		(0.003)	
Log(Rate Exposure-Export)		0.083***		0.082***		−0.001		0.030***		0.030***		−0.004
		(0.007)		(0.007)		(0.002)		(0.007)		(0.007)		(0.003)
Log(Rate Exposure-Import)		−0.019***		−0.024***		0.002		0.071***		0.060***		0.021***
		(0.006)		(0.007)		(0.002)		(0.006)		(0.007)		(0.003)
Year-City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	77,578	77,578	77,578	77,578	76,980	76,980	77,578	77,578	77,578	77,578	76,980	76,980
R^2	0.670	0.671	0.635	0.635	0.470	0.470	0.635	0.635	0.662	0.662	0.562	0.562

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–12 report the coefficient estimates from the regression Equation (5) for logged values of the city-sector level trade outcomes: the total values, volumes, and unit prices of total exports and total imports. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Standard errors in parentheses are clustered at the city level.

Table 4: Carbon Price Exposure and Pollution in China

	Pollution Outcomes											
	Carbon		Wastewater		NO_x		SO_2		Particulate		PM2.5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Exposure-Export)	0.001		0.010		-0.018^{*}		-0.083		-0.011		0.003^{***}	
	(0.003)		(0.008)		(0.011)		(0.120)		(0.011)		(0.001)	
Log(Exposure-Import)	-0.004^{***}		-0.010^{*}		-0.018^{**}		-0.229^{**}		-0.006		-0.004^{***}	
	(0.001)		(0.006)		(0.007)		(0.098)		(0.008)		(0.001)	
Log(Rate Exposure-Export)		0.0003		0.017		-0.028^{**}		-0.017		-0.011		0.005^{***}
		(0.003)		(0.012)		(0.012)		(0.117)		(0.012)		(0.002)
Log(Rate Exposure-Import)		-0.005^{***}		-0.015^{**}		-0.023^{***}		-0.212^{**}		-0.012		-0.005^{***}
		(0.002)		(0.008)		(0.008)		(0.106)		(0.010)		(0.001)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,789	3,789	4,211	4,211	4,454	4,454	2,292	2,292	4,449	4,449	4,605	4,605
R^2	0.989	0.989	0.872	0.872	0.824	0.825	0.901	0.901	0.728	0.728	0.961	0.961

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–12 report the coefficient estimates from the regression Equation (4) for logged values of the city-level environmental outcomes: estimates of total carbon emissions, yearly total wastewater, NO_x, SO_2, particulates discharges, and yearly average estimated PM2.5 levels. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 338 unique prefectures in China from 2000 to 2020. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions. Standard errors in parentheses are clustered at the city level.

Table 5: Mechanism Analysis: Tradable Sectors

	Dependent variable (tradables):			
	Log(Penalty Number)	Log(Penalty Sum)	Log(Penalty Number)	Log(Penalty Sum)
	(1)	(2)	(3)	(4)
Log(Exposure-Export)	0.019***	0.006**		
	(0.003)	(0.002)		
Log(Exposure-Import)	0.0002	−0.004*		
	(0.002)	(0.002)		
Log(Rate Exposure-Export)			0.023***	0.007***
			(0.003)	(0.002)
Log(Rate Exposure-Import)			0.002	−0.005*
			(0.003)	(0.003)
Year-City FE	Y	Y	Y	Y
Year-Sector FE	Y	Y	Y	Y
Observations	17,161	15,587	17,161	15,587
R^2	0.613	0.402	0.615	0.402

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–4 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 23 unique tradable sectors, mainly based on Chinese sector categorization, and 337 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Standard errors in parentheses are clustered at the city level.

Table 6: Mechanism Analysis: Non-tradable Sectors

	Dependent variable (non-tradables):			
	Log(Penalty Number)	Log(Penalty Sum)	Log(Penalty Number)	Log(Penalty Sum)
	(1)	(2)	(3)	(4)
Log(Exposure-Export)	0.040	−0.107		
	(0.100)	(0.213)		
Log(Exposure-Import)	0.212**	0.455***		
	(0.086)	(0.155)		
Log(Rate Exposure-Export)			0.203***	−0.069
			(0.071)	(0.184)
Log(Rate Exposure-Import)			0.160**	0.174
			(0.077)	(0.139)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City Controls	Y	Y	Y	Y
Observations	7,500	6,940	7,500	6,940
R^2	0.281	0.103	0.282	0.101

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–4 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 14 unique non-tradable sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Standard errors in parentheses are clustered at the city level.

Appendices

A Data Details

A.1 European Carbon Prices

We obtain European carbon price data from the World Carbon Pricing Database hosted by Resources for the Future (RFF)[16] (Dolphin and Xiahou, 2022). Specifically, we use carbon price data from 2000 to 2020 for 32 countries, including all 27 current EU member states, the UK, Switzerland, Iceland, Liechtenstein, and Norway—covering all countries participating in the EU ETS during this period and Switzerland. The carbon prices are provided at the jurisdiction-sector level, with yearly averages of daily prices in local currency units. We also unify all carbon prices at the EU ETS and the Swiss ETS as 2015 Euros, using the GDP deflator index and currency exchange rates data from the World Bank database[17].

It is noticeable that the EU ETS and the Swiss ETS are not the only operating cap-and-trade system in the world during this period. According to the State and Trends of Carbon Pricing Dashboard updated by the World Bank [18] as well as the carbon price data source we use, there are New Zealand ETS, Kazakhstan ETS, (South) Korea ETS, Canada federal OBPS, Mexico pilot ETS already implemented before 2020 at the national level, and much more at the subnational levels in the US, Canada, and in China. To simplify our analysis and to focus on EU ETS, the earliest, one of the largest, and arguably the most successful cap-and-trade systems, we ignore all other regimes and consider the carbon prices all as zero during the whole period.

The EU ETS carbon price data in the World Carbon Pricing Database originates from the Allowance Price Explorer of the International Carbon Action Partnership (ICAP), which provides European Union Allowance (EUA) spot price data from the European Energy Exchange (EEX) Group. Swiss ETS prices are calculated based on auction clearing prices and allowances sold by the Swiss Emissions Trading Registry.

The carbon prices by country and sector in the World Carbon Pricing Database are disaggregated using the Intergovernmental Panel on Climate Change (IPCC) source and

[16] https://www.rff.org/publications/data-tools/world-carbon-pricing-database/; database available at https://github.com/g-dolphin/WorldCarbonPricingDatabase

[17] See the website https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS?skipRedirection=true&view=map for more details

[18] See the website https://carbonpricingdashboard.worldbank.org/ for more detials

sector categories.[19]

A.2 Input-Output Tables

To calculate the embodied carbon price burden within the EU—including both direct carbon costs and indirect costs through industrial processes—we use the multi-regional input-output (MRIO) tables from EXIOBASE, specifically EXIOBASE version 3.8.2, updated on October 21, 2021.[20] EXIOBASE 3 provides a time series of environmentally extended MRIO (EE MRIO) tables for 44 countries and five rest-of-the-world regions from 1995 onward, with data presented in millions of current euros. We utilize annual tables to capture key sectors, obtaining the input-output matrix A, the final demand matrix C, the total output vector Y, and the emission intensity vector E from tables A, Y, x, and D_{pda}, respectively. The embodied emission rates are calculated as $E(I - A)^{-1}$, and the total embodied emissions are given by $E(I - A)^{-1}C$.

EXIOBASE employs its own industry and product classification system, encompassing 163 industries and 200 products.

A.3 Sector Concordance

We employ several concordance tables to harmonize sector categories across different classification systems, using the EXIOBASE sector classification as our baseline. First, we align the IPCC sectors from the carbon price data with the EXIOBASE sectors, which requires two concordance tables. One converts EXIOBASE codes to ISIC Rev.3 codes, provided by the EXIOBASE research team,[21] and the other converts ISIC Rev.4 codes to IPCC codes, included in the World Carbon Pricing Database.[22] To complete the concordance, we also use tables converting ISIC Rev.3 to ISIC Rev.4 codes from the United Nations Statistics Division (UNSD) Classifications on Economic Statistics.[23]

Due to many-to-many relationships between IPCC codes and EXIOBASE sector codes, some EXIOBASE sectors correspond to multiple IPCC codes with different carbon prices.

[19] https://www.ipcc.ch/report/2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/

[20] https://zenodo.org/record/5589597

[21] All concordance tables mentioned are available at https://ntnu.app.box.com/v/EXIOBASEconcordances/file/282981251742.

[22] https://github.com/g-dolphin/WorldCarbonPricingDatabase/tree/main/_aux_files/classifications_concordances

[23] https://unstats.un.org/unsd/classifications/Econ

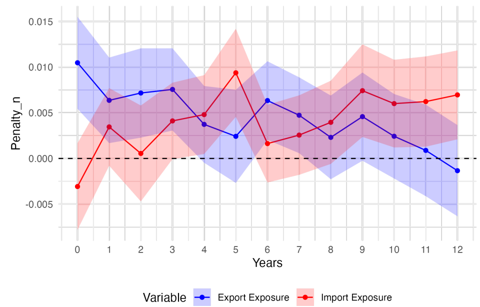
We manually matched and verified all concordances to generate country-year-sector-specific carbon prices using the EXIOBASE sector classification.

Second, we align the EXIOBASE sector codes with the Harmonized System (HS) codes in China's customs data. We use a bridge file between HS codes (version 1996) and EXIOBASE 2 codes provided by the EXIOBASE project team. We also convert HS codes from each year to HS 1996 using concordance tables provided by the UNSD. We manually check and amend the concordance between HS 1996 codes and EXIOBASE 2.0 codes when necessary.

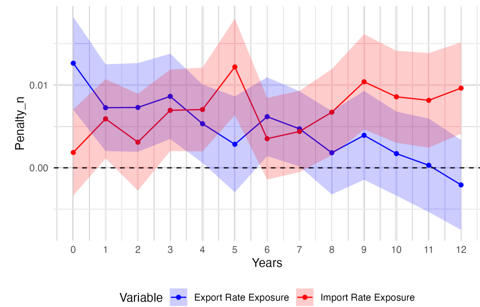
Finally, we handle penalty data containing sector information based on China's industrial classification categories. We concord the EXIOBASE sectors with Chinese sectors using a concordance table between Chinese industrial classifications and EXIOBASE codes, also provided by the EXIOBASE team.

B Figures

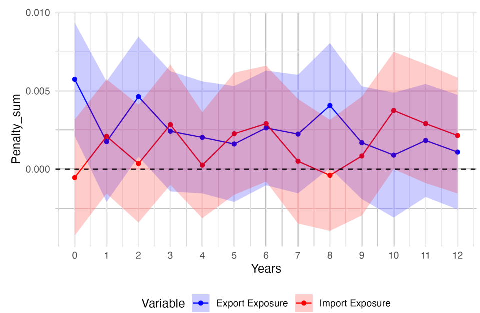
Figure B.1: Dynamic Impacts on Environmental Regulations



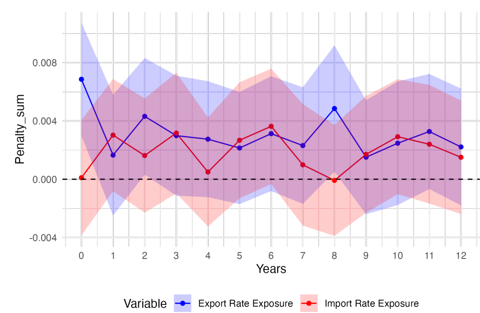
(a) Number of Penalties



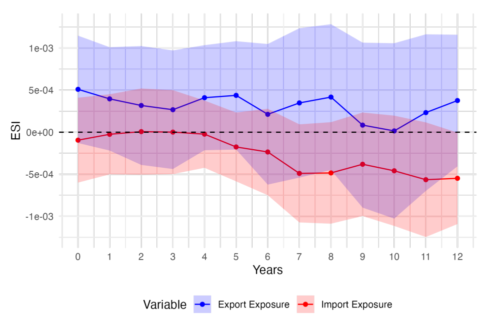
(b) Number of Penalties



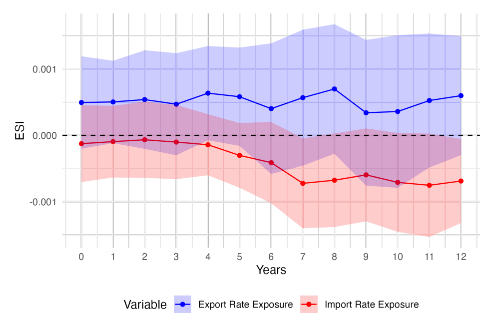
(c) Sum of Penalties



(d) Sum of Penalties



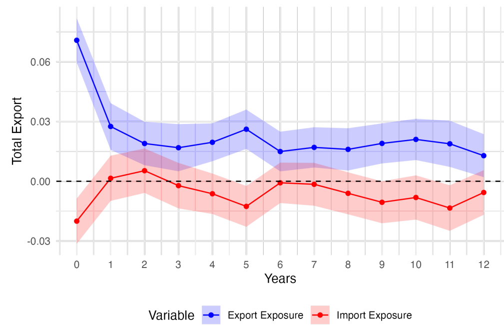
(e) ESI



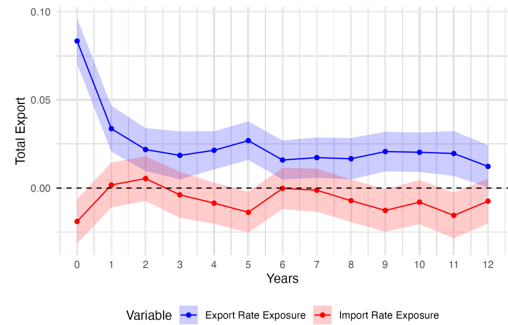
(f) ESI

Note: Figures report the coefficient estimates from the regression Equation (7) for logged values of the environmental regulation outcomes: number of penalties, sum of penalties, and city-level environmental regulation stringency index (ESI). The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. City-year and sector-year fixed effects are included, and standard errors are clustered at the city level. The solid line is the point estimate, and the blue and red shaded areas are 90 percent confidence bands of export-weighted and import-weighted exposures dynamic coefficients estimates, respectively.

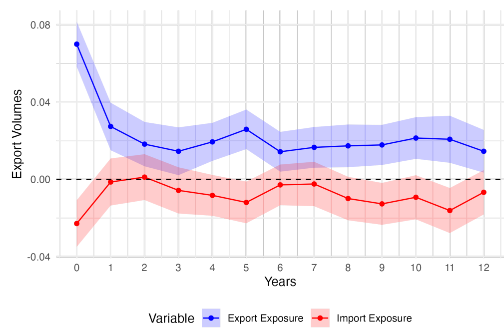
Figure B.2: Dynamic Impacts on Export



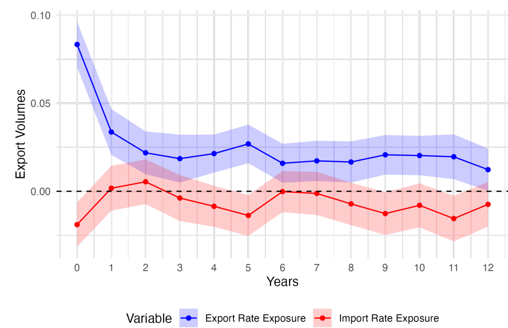
(a) Export Values



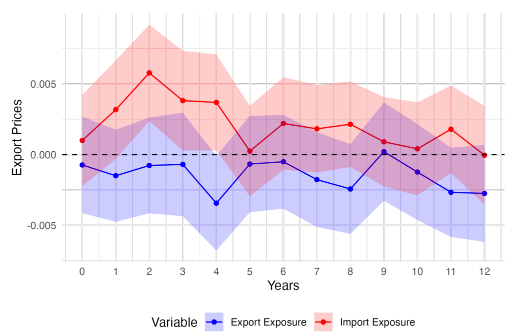
(b) Export Values



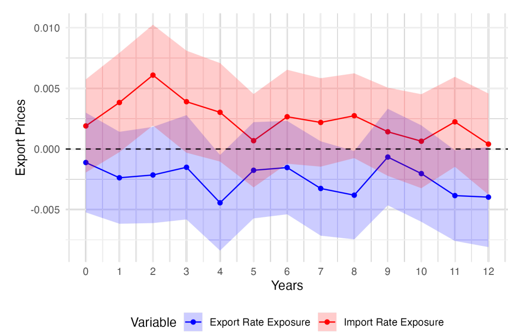
(c) Export Volumes



(d) Export Volumes



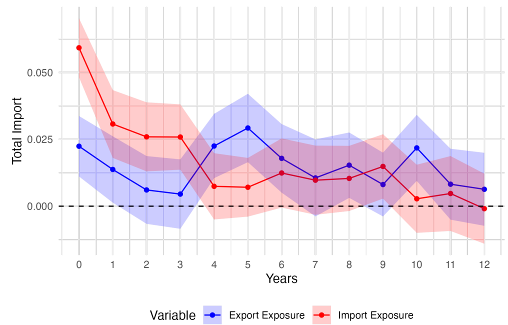
(e) Export Unit Prices



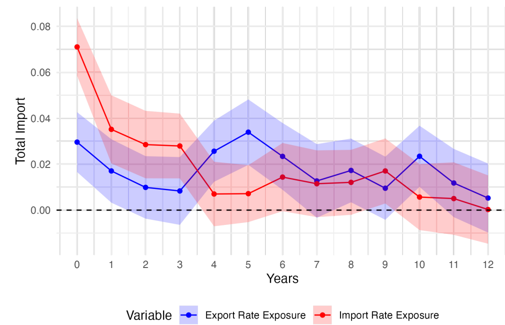
(f) Export Unit Price

Note: Figures report the coefficient estimates from the regression Equation (7) for logged values of the total export values, total export volumes, and export unit prices. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. City-year and sector-year fixed effects are included, and standard errors are clustered at the city level. The solid line is the point estimate, and the blue and red shaded areas are 90 percent confidence bands of export-weighted and import-weighted exposures dynamic coefficients estimates, respectively.

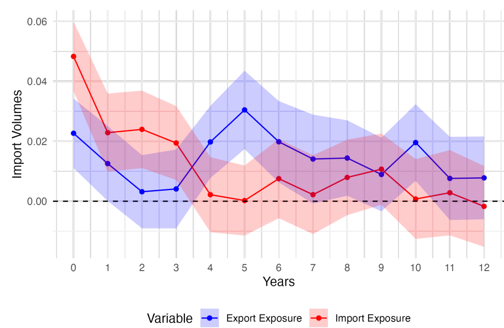
Figure B.3: Dynamic Impacts on Import



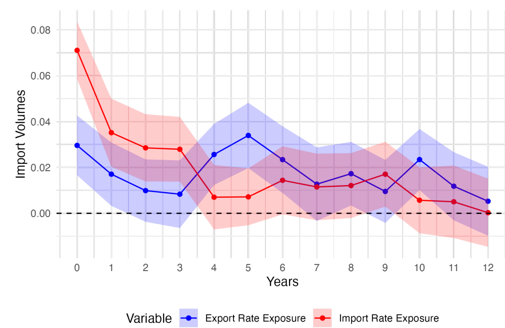
(a) Import Values



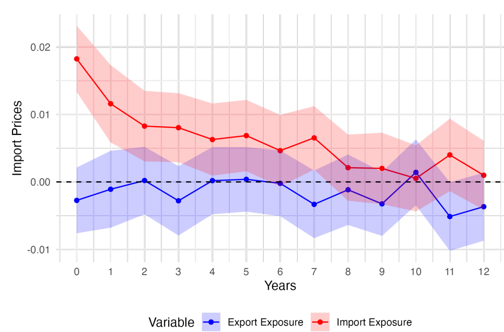
(b) Import Values



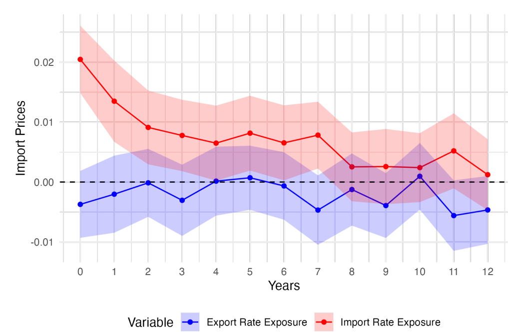
(c) Import Volumes



(d) Import Volumes



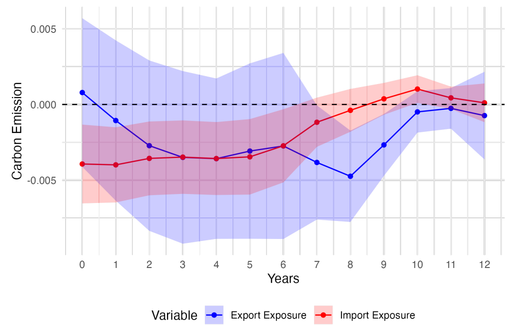
(e) Import Unit Prices



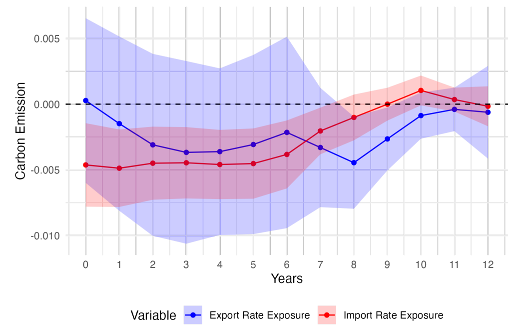
(f) Import Unit Price

Note: Figures report the coefficient estimates from the regression Equation (7) for logged values of the total export values, total export volumes, and export unit prices. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. City-year and sector-year fixed effects are included, and standard errors are clustered at the city level. The solid line is the point estimate, and the blue and red shaded areas are 90 percent confidence bands of export-weighted and import-weighted exposures dynamic coefficients estimates, respectively.

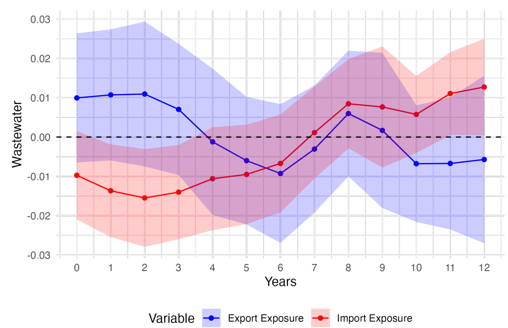
Figure B.4: Dynamic Impacts on Environmental Outcomes



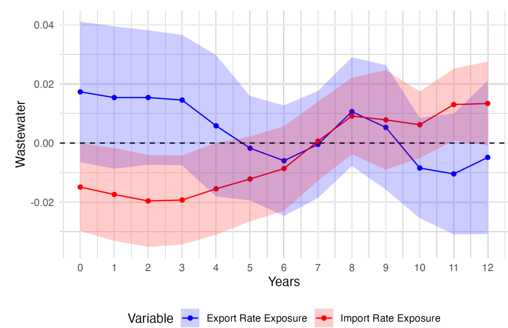
(a) Carbon Emissions



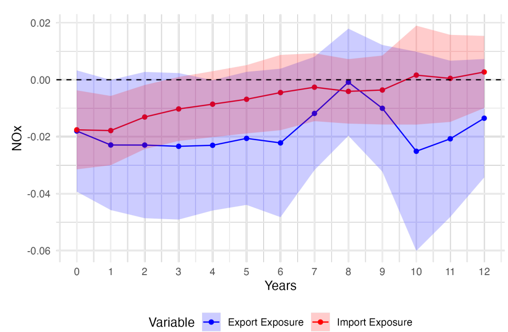
(b) Carbon Emissions



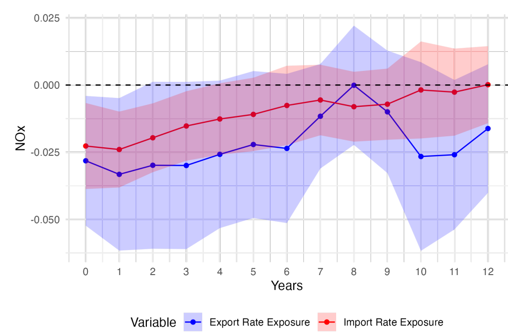
(c) Wastewater



(d) Wastewater



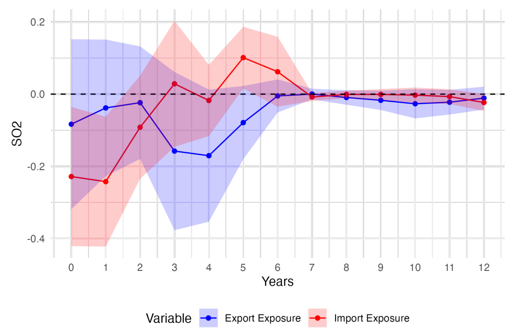
(e) NO_x



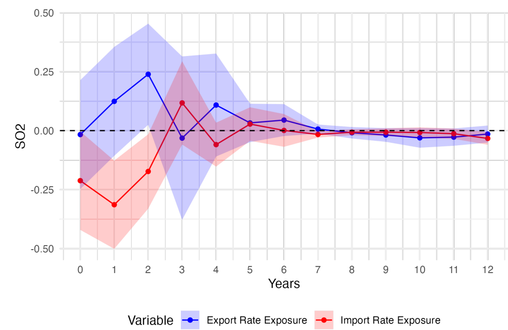
(f) NO_x

Note: Figures report the coefficient estimates from the regression Equation (6) for logged values of city-level carbon emissions, wastewater discharges, and NO_x discharges. The independent variables are Chinese city-level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 338 unique prefectures in China from 2000 to 2020. City and sector fixed effects are included, and standard errors are clustered at the city level. The solid line is the point estimate, and the blue and red shaded areas are 90 percent confidence bands of export-weighted and import-weighted exposures dynamic coefficients estimates, respectively.

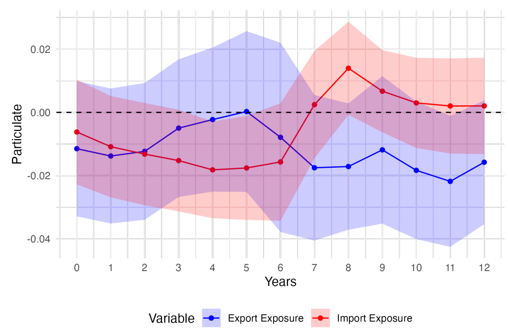
Figure B.5: Dynamic Impacts on Environmental Outcomes (Continued)



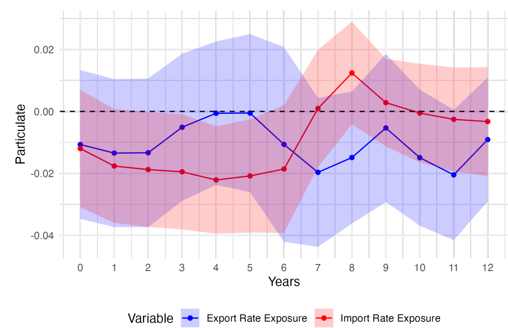
(a) SO_2



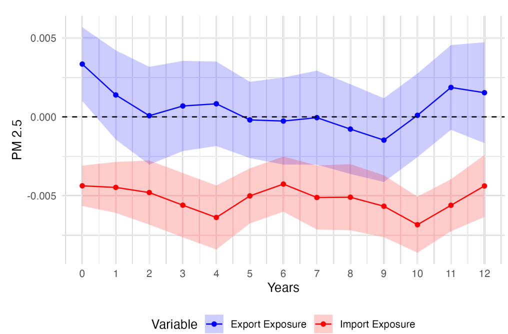
(b) SO_2



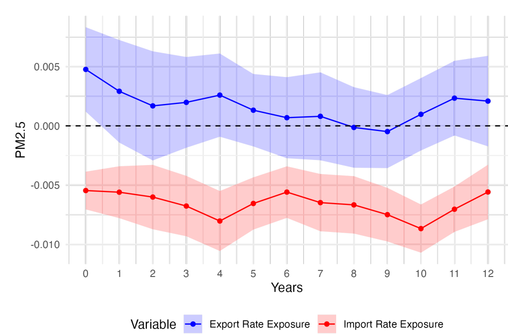
(c) Particulate



(d) Particulate



(e) PM2.5



(f) PM2.5

Note: Figures report the coefficient estimates from the regression Equation (6) for logged values of city-level SO_2 emissions, industrial particulate discharges, and yearly average PM2.5 levels. The independent variables are Chinese city-level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 338 unique prefectures in China from 2000 to 2020. City and sector fixed effects are included, and standard errors are clustered at the city level. The solid line is the point estimate, and the blue and red shaded areas are 90 percent confidence bands of export-weighted and import-weighted exposures dynamic coefficients estimates, respectively.

C Tables

Table C.1: Robustness Checks: Different FE

	Dependent variable:			
	Log(Penalty Number)		Log(Penalty Sum)	
	(1)	(2)	(3)	(4)
Log(Exposure-Export)	0.012***	0.013***	0.006***	0.007***
	(0.003)	(0.003)	(0.002)	(0.002)
Log(Exposure-Import)	−0.002	−0.003	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Y		Y	
City FE	Y		Y	
Sector FE	Y	Y	Y	Y
Year-City FE		Y		Y
Observations	27,074	27,074	24,664	24,664
R^2	0.483	0.571	0.246	0.374

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–4 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique tradable sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. We include two different sets of fixed effects in the regressions: (1) year fixed effects, sector fixed effects, and city fixed effects, and (2) sector fixed effects and city-year fixed effects. Standard errors, reported in parentheses, are clustered at the city level. Standard errors in parentheses are clustered at the city level.

Table C.2: Robustness Checks: Different FE (Continued)

	Dependent variable:											
	Log(Value)		Log(Volume) Export		Log(Prices)		Log(Value)		Log(Volume) Import		Log(Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Exposure-Export)	0.029***	0.042***	0.027***	0.040***	−0.001	0.002*						
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)						
Log(Rate Exposure-Export)							0.030***	0.039***	−0.003	0.005	0.028***	0.033***
							(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)
Year FE	Y		Y		Y		Y		Y		Y	
City FE	Y		Y		Y		Y		Y		Y	
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-City FE		Y		Y		Y		Y				
Observations	76,786	76,786	76,786	76,786	76,212	76,212	76,786	76,786	76,786	76,786	76,212	76,212
R^2	0.576	0.624	0.534	0.584	0.404	0.454	0.571	0.618	0.595	0.632	0.495	0.539

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–12 report the coefficient estimates from the regression Equation (5) for logged values of the city-sector level trade outcomes: the total values, volumes, and unit prices of total exports and total imports. The independent variables are Chinese city-sector level logged values of the export-weighted and import-weighted exposure to the carbon total cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. We include two different sets of fixed effects in the regressions: (1) year fixed effects, sector fixed effects, and city fixed effects, and (2) sector fixed effects and city-year fixed effects. Standard errors, reported in parentheses, are clustered at the city level. Standard errors in parentheses are clustered at the city level.

Table C.3: Robustness Checks: Using Lags

	Dependent variable:					
	Log(Penalty Number)	Log(Penalty Sum)	ESI	Log(Penalty Number)	Log(Penalty Sum)	ESI
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Log(Exposure-Export)	0.011***	0.005*	0.0004			
	(0.003)	(0.003)	(0.0003)			
Lag Log(Exposure-Import)	−0.006**	−0.0001	−0.00004			
	(0.003)	(0.003)	(0.0003)			
Lag Log(Rate Exposure-Export)				0.013***	0.006**	0.0005
				(0.003)	(0.003)	(0.0003)
Lag Log(Rate Exposure-Import)				−0.0002	0.0001	−0.0001
				(0.003)	(0.003)	(0.0003)
Year FE			Y			Y
City FE			Y			Y
Year-City FE	Y	Y		Y	Y	
Year-Sector FE	Y	Y		Y	Y	
Controls			Y			Y
Observations	21,220	20,050	4,889	21,220	20,050	4,598
R^2	0.630	0.396	0.479	0.630	0.396	0.485
Adjusted R^2	0.586	0.322	0.446	0.586	0.322	0.450

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1, 2, 4, and 5 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are the Chinese city-sector level first-period lagged logged values of the export-weighted and import-weighted exposure to the total carbon cost or cost rates in the EU. Columns 3 and 6 report the estimates from regression Equation (4) for the logged values of the city-level environmental regulation stringency index (ESI). The independent variable is the city-level weighted sums of four exposures to the EU carbon prices. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions on city-level outcomes. Standard errors in parentheses are clustered at the city level.

Table C.4: Robustness Checks: Using Lags (Continued)

	Dependent variable:											
	Log(Value)		Log(Volume) Export		Log(Prices)		Log(Value)		Log(Volume) Import		Log(Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag Log(Exposure-Export)	0.053***		0.053***		−0.002		0.022***		0.022***		−0.003	
	(0.005)		(0.005)		(0.002)		(0.006)		(0.006)		(0.003)	
Lag Log(Rate Exposure-Export)	−0.013**		−0.015***		0.0005		0.046***		0.037***		0.015***	
	(0.005)		(0.006)		(0.002)		(0.006)		(0.006)		(0.003)	
Lag Log(Exposure-Import)		0.063***		0.063***		−0.002		0.028***		0.029***		−0.004
		(0.006)		(0.006)		(0.002)		(0.007)		(0.007)		(0.003)
Lag Log(Rate Exposure-Import)		−0.012*		−0.015**		0.001		0.056***		0.047***		0.017***
		(0.006)		(0.006)		(0.002)		(0.007)		(0.007)		(0.003)
Year-City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	71,016	71,016	71,016	71,016	70,464	70,464	71,016	71,016	71,016	71,016	70,464	70,464
R^2	0.670	0.670	0.635	0.635	0.473	0.473	0.636	0.636	0.666	0.666	0.560	0.560

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–12 report the coefficient estimates from the regression Equation (5) for logged values of the city-sector level trade outcomes: the total values, volumes, and unit prices of total exports and total imports. The independent variables are the first-period lagged logged values of the export-weighted and import-weighted exposure of the Chinese city-sector level to the total carbon cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Standard errors in parentheses are clustered at the city level.

Table C.5: Robustness Checks: Using Lags (Continued)

	Pollution Outcomes											
	Carbon		Wastewater		NO_x		SO_2		Particulate		PM2.5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag Log(Exposure-Export)	−0.0002		0.009		−0.023**		0.001		−0.013		0.002*	
	(0.003)		(0.008)		(0.011)		(0.085)		(0.011)		(0.001)	
Lag Log(Exposure-Import)	−0.004***		−0.012*		−0.016**		−0.176**		−0.007		−0.005***	
	(0.001)		(0.006)		(0.007)		(0.078)		(0.009)		(0.001)	
Lag Log(Rate Exposure-Export)		−0.001		0.012		−0.034**		0.174		−0.016		0.004**
		(0.003)		(0.011)		(0.014)		(0.115)		(0.012)		(0.002)
Lag Log(Rate Exposure-Import)		−0.005***		−0.015**		−0.022***		−0.203**		−0.013		−0.006***
		(0.002)		(0.008)		(0.007)		(0.080)		(0.010)		(0.001)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,789	3,789	4,211	4,211	4,454	4,454	2,292	2,292	4,449	4,449	4,605	4,605
R^2	0.989	0.989	0.872	0.872	0.825	0.826	0.901	0.901	0.728	0.728	0.961	0.961

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Columns 1–12 report the coefficient estimates from the regression Equation (4) for logged values of the city-level environmental outcomes: estimates of total carbon emissions, yearly total wastewater, NO_x, SO_2, particulates discharges, and yearly average estimated PM2.5 levels. The independent variables are the first-period lagged logged values of the export-weighted and import-weighted exposure of the Chinese city-sector level to the total carbon cost or cost rates in the EU. The samples include 338 unique prefectures in China from 2000 to 2020. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions. Standard errors in parentheses are clustered at the city level.

Table C.6: Robustness Checks: Using MA(3)

	Dependent variable:					
	Log(Penalty Number)	Log(Penalty Sum)	ESI	Log(Penalty Number)	Log(Penalty Sum)	ESI
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Exposure-Export, MA3)	0.007**	0.001	0.0005			
	(0.004)	(0.003)	(0.0003)			
Log(Exposure-Import, MA3)	−0.005	0.001	−0.0001			
	(0.003)	(0.003)	(0.0003)			
Log(Rate Exposure-Export, MA3)				0.010**	0.002	0.001
				(0.004)	(0.003)	(0.0004)
Log(Rate Exposure-Import, MA3)				0.001	0.002	−0.0001
				(0.003)	(0.003)	(0.0003)
Year FE			Y			Y
City FE			Y			Y
Year-City FE	Y	Y		Y	Y	
Year-Sector FE	Y	Y		Y	Y	
Controls			Y			Y
Observations	15,043	14,531	4,889	15,043	14,531	4,598
R^2	0.652	0.414	0.479	0.653	0.414	0.485

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1, 2, 4, and 5 report the coefficient estimates from the regression Equation (5) for two logged values of the city-sector level outcomes: the total number and sum of values of environmental penalties. The independent variables are the Chinese city-sector level three-year moving average (average of the current, the one-year lagged, and the two-year lagged values) of the logged values of the export-weighted and import-weighted exposure to the total carbon cost or cost rates in the EU. Columns 3 and 6 report the estimates from regression Equation (4) for the logged values of the city-level environmental regulation stringency index (ESI). The independent variable is the city-level weighted sums of four exposures to the EU carbon prices. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions on city-level outcomes. Standard errors in parentheses are clustered at the city level.

Table C.7: Robustness Checks: Using MA(3) (Continued)

	Dependent variable:											
	Log(Value)		Log(Volume) Export		Log(Prices)		Log(Value)		Log(Volume) Import		Log(Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Exposure-Export, MA3)	0.052***		0.052***		−0.001		0.022***		0.022***		−0.003	
	(0.005)		(0.005)		(0.002)		(0.006)		(0.006)		(0.003)	
Log(Exposure-Import, MA3)	−0.015***		−0.017***		0.0004		0.044***		0.035***		0.015***	
	(0.005)		(0.006)		(0.002)		(0.006)		(0.006)		(0.003)	
Log(Rate Exposure-Export, MA3)		0.062***		0.061***		−0.002		0.028***		0.029***		−0.004
		(0.006)		(0.006)		(0.002)		(0.006)		(0.006)		(0.003)
Log(Rate Exposure-Import, MA3)		−0.013**		−0.016**		0.001		0.054***		0.045***		0.017***
		(0.006)		(0.006)		(0.002)		(0.007)		(0.007)		(0.003)
Year-City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	58,491	58,491	58,491	58,491	58,044	58,044	58,491	58,491	58,491	58,491	58,044	58,044
R^2	0.676	0.676	0.643	0.643	0.489	0.489	0.643	0.644	0.676	0.676	0.553	0.553

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Columns 1–12 report the coefficient estimates from the regression Equation (5) for logged values of the city-sector level trade outcomes: the total values, volumes, and unit prices of total exports and total imports. The independent variables are the three-year moving average (average of the current, the one-year lagged, and the two-year lagged values) of the logged values of the export-weighted and import-weighted exposure of the Chinese city-sector level to the total carbon cost or cost rates in the EU. The samples include 37 unique sectors, mainly based on Chinese sector categorization, and 338 unique prefectures in China from 2000 to 2020. Year-city fixed effects and year-sector fixed effects are included in the city-sector regressions. Standard errors in parentheses are clustered at the city level.

Table C.8: Robustness Checks: Using MA(3) (Continued)

	Pollution Outcomes											
	Carbon		Wastewater		NO_x		SO_2		Particulate		PM2.5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Exposure-Export, MA3)	0.001		0.010		−0.018*		−0.036		−0.011		0.004***	
	(0.003)		(0.009)		(0.011)		(0.139)		(0.011)		(0.001)	
Log(Exposure-Import, MA3)	−0.004***		−0.010*		−0.018**		−0.273**		−0.006		−0.004***	
	(0.001)		(0.006)		(0.007)		(0.114)		(0.009)		(0.001)	
Log(Rate Exposure-Export, MA3)		0.0001		0.017		−0.027**		0.295		−0.012		0.005***
		(0.003)		(0.013)		(0.013)		(0.185)		(0.012)		(0.002)
Log(Rate Exposure-Import, MA3)		−0.005***		−0.015*		−0.023***		−0.358***		−0.012		−0.005***
		(0.002)		(0.008)		(0.008)		(0.127)		(0.010)		(0.001)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,789	3,789	4,211	4,211	4,454	4,454	2,292	2,292	4,449	4,449	4,605	4,605
R^2	0.989	0.989	0.872	0.872	0.824	0.825	0.901	0.901	0.728	0.728	0.961	0.961

*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1–12 report the coefficient estimates from the regression Equation (4) for logged values of the city-level environmental outcomes: estimates of total carbon emissions, yearly total wastewater, NO_x, SO_2, particulates discharges, and yearly average estimated PM2.5 levels. The independent variables are the three-year moving average (average of the current, the one-year lagged, and the two-year lagged values) of the logged values of the export-weighted and import-weighted exposure of the Chinese city-sector level to the total carbon cost or cost rates in the EU. The samples include 338 unique prefectures in China from 2000 to 2020. Year fixed effects, city fixed effects, and city-level controls, including logged values of GDP per capita and registered total population, are included in the regressions. Standard errors in parentheses are clustered at the city level.