Climate Policy

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tcpo20

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To cite this article: Jie-Sheng Tan-Soo, Lili Li, Ping Qin & Xiao-bing Zhang (2021): Do CO_2 emissions trading schemes deliver co-benefits? evidence from shanghai, Climate Policy, DOI: 10.1080/14693062.2021.2009432

To link to this article: https://doi.org/10.1080/14693062.2021.2009432

CLIMATE POLICY
https://doi.org/10.1080/14693062.2021.2009432

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RESEARCH ARTICLE

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Do CO_2 emissions trading schemes deliver co-benefits? evidence from shanghai

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ABSTRACT

While ex-*ante* evaluations of climate mitigation policies predict that co-benefits of improved air quality will enable the aggregate benefits of climate mitigation policies to outweigh their costs, there is little empirical evidence to support this assertion. In this study, we use data on weekly smokestack emissions of sulfur dioxide (SO_2) from firms participating in Shanghai's carbon dioxide (CO_2) emissions trading scheme (ETS) to deliver one of the first ex-*post* evaluations on the co-benefits of China's ETS. Using a panel-regression model in which all firms' characteristics and seasonal effects are controlled, we find a significant negative association between CO_2 emissions prices and industrial SO_2 emissions (elasticity of −0.13). A closer examination reveals that most of these effects were driven by specific sectors (iron and steel) and during months in which firms were required to balance their annual CO_2 emissions. To ensure our results are not driven by confounding factors and our model's assumptions, we conducted several falsification checks using SO_2 emissions from non-ETS firms and firms from a nearby city, using various model specifications. Our findings suggest that co-benefits from climate mitigation policies should not be taken for granted, and that policy designs and types of sector sources of emissions are important determinants of co-benefits.

Key policy insights:

- The study provides empirical evidence for air pollution co-benefits of a CO_2 ETS using weekly smokestack-level data from Shanghai, China
- Evidence from the Shanghai ETS shows that a 1% increase in CO_2 prices in Shanghai is associated with a 0.13% decrease in SO_2 emissions
- These co-benefits, however, are limited to specific sectors (e.g. ferrous metals), and are not found in other major CO_2 emitting sources or sectors (e.g. power utilities)
- The relationship between CO_2 prices and co-benefits is also stronger during months in which firms are required to balance their annual CO_2 emissions using permits

ARTICLE HISTORY
Received 14 January 2021
Accepted 16 November 2021

KEYWORDS
Air pollution abatement; co-benefits; CO_2 emissions; emissions trading schemes; policy design and implementation

1. Introduction

One of the main impediments to more aggressive climate mitigation policies is that while the climate-related benefits of reducing greenhouse gas (GHG) emissions are distributed globally, the costs are borne almost entirely locally (Nemet et al., 2010; Somanathan et al., 2014).[1] This misalignment of costs and benefits has prompted scholars and policymakers to consider using 'co-benefits' to justify ambitious climate actions. The rationale behind co-benefits in climate mitigation policies can be understood in the following manner. First,

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Supplemental data for this article can be accessed https://doi.org/10.1080/14693062.2021.2009432.

many processes that produce large amounts of GHG are also major emitters of air pollutants; for example, fossil fuel combustion emits both carbon dioxide (CO_2) and non-GHG air pollutants such as sulfur dioxide (SO_2) and nitrous oxides (NO_X) (IEA, 2016; IPCC, 2014; Perera, 2017; Quéré et al., 2018).[2] In this regard, it is likely that policies that reduce GHG emissions will have the dual effects of reducing co-emitted air pollutants. This reduction in co-emitted air pollutants would then induce near-term local public health benefits (e.g. the reduction of SO_2 and NO_X, which are major causes of respiratory illnesses) even though the underlying policy specifically targets GHG emissions (Cai et al., 2016; Cheng et al., 2015; Driscoll et al., 2015; Jiang et al., 2013; Karlsson et al., 2020; Li et al., 2018; Nemet et al., 2010; Thompson et al., 2014; West et al., 2013). This implies that policies designed to reduce GHG emissions could potentially deliver local dividends that should be part of the cost–benefit accounting of climate mitigation policies.

While co-benefits sound like attractive propositions, there is insufficient empirical evidence to support their inclusion in policy considerations. Until now, due to the lack of existing policies and data, most studies on air quality-related co-benefits have relied either on assumptions-laden simulated models or qualitative descriptions (e.g. Cheng et al., 2015; Li et al., 2018; Thompson et al., 2014). However, the latest IPCC Assessment Report and other literature have highlighted that empirical evidence of co-benefits of climate mitigation policies is a key knowledge gap and is sorely needed by policymakers to justify costly climate policies (Karlsson et al., 2020; Somanathan et al., 2014). One reason is that simulated models that predict the existence of co-benefits are often based on stylized or first-best scenarios in which programmes are optimally designed and firms behave predictably (Cheng et al., 2015; Karlsson et al., 2020; Li et al., 2018; Thompson et al., 2014). In practice, there is likely to be significant heterogeneity in co-benefits due to variations in income levels, programme designs, and spatial locations – all of which cannot be comprehensively included in simulated models (Nemet et al., 2010; Woollacott, 2018).

To this end, this study uses a panel dataset of pollutant emissions from industrial firms in the Chinese mega-city of Shanghai to examine the co-benefits of a major climate mitigation policy. Specifically, we investigate whether the CO_2 emissions trading scheme (ETS) reduces firms' SO_2 emissions, as predicted by most simulation models. We arrive at the following findings using fixed-effects regressions. First, we observe that ETSs do indeed deliver co-benefits, as a 1% increase in CO_2 prices is associated with a 0.13% decrease in firm-level SO_2 emissions. Second, heterogeneity analyses revealed that co-benefits are not widespread. We find that impacts are mostly driven by the ferrous metal industry as opposed to other major polluters such as power utilities (i.e. electricity and heating plants). The impacts are also more strongly observed during the CO_2 'auditing' months during which firms pay more attention toward gathering sufficient emissions permits to cover emissions. Taken together, these findings imply that policy design and implementation are key determinants of co-benefits.

1.1. Background on China's emissions trading schemes

China became the world's largest GHG emitter in 2012, and pledged in the 2015 Paris Agreement to reduce its CO_2 emission intensity by 60%–65% in 2030 relative to the 2005 level (NDRC, 2015). Most recently, China announced an ambitious goal of achieving carbon neutrality by 2060 (Mallapaty, 2020). To fulfil these commitments, China has adopted many climate mitigation policies, of which the CO_2 ETS is one of the largest (Li & Wang, 2011; Nejat et al., 2015). The ETS functions by first establishing a total CO_2 emissions cap for all regulated firms. Regulated firms respond to this cap by either reducing their emissions, purchasing emissions permits from other firms, or a combination of the two. The ETS makes it costly for firms to emit CO_2, and the extent to which firms respond to this policy is a function of the emissions permit price (we illustrate this concept in greater detail in a later section).

Until now, thirty-one local, national or regional ETSs have been implemented or are scheduled for implementation, among which the European Union (EU) ETS is currently the largest CO_2 ETS (World Bank, 2020). Since 2013, China has developed seven independent CO_2 ETS pilots in the cities of Beijing, Tianjin, Shanghai, Chongqing, and Shenzhen and the provinces of Hubei and Guangdong. While these ETS pilots share policy designs, such as an intensity-based cap, the inclusion of the electricity sector, and the use of free allocation, there are also variations in terms of non-compliance penalties, sectoral coverage, and permit allocations. The Chinese government's goal is to gather evidence of policy effectiveness and implementation experience from these pilot schemes and feed them into the design of a national-level ETS, which was soft-launched in December 2017, and recently began operations in July 2021 (NDRC, 2015).[3]

Other than meeting abatement commitments, the ETS and other GHG mitigation policies are consistent with China's domestic goals of moving toward renewable energy sources and improving air quality (Schreurs, 2016). This is because, first, China is dependent on coal (which accounts for around 70% of China's CO_2 emissions[4]) to meet about 58% of primary energy consumption needs, and to generate more than half of its total electricity consumption.[5] Second, coal combustion not only emits GHGs, but is also estimated to be responsible for about 90% of SO_2 emissions, 67% of NO_x emissions, and 70% of particulate matter emissions (Chen & Xu, 2010). Hence, it is hopeful that an ETS will add to the cost of coal usage and prompt firms to move towards alternative sources of energy that emit less CO_2 and air pollutants.

While evidence of the effectiveness of China's ETS in reducing CO_2 emissions is emerging, there are still no studies that examine its co-benefits (Tang et al., 2020; Zhang et al., 2019a; Zhang et al., 2019b). We address this research gap by examining the influence of ETS policy on industrial firms' air pollution over the period from 2014 to 2016.

To this end, we chose to study the Shanghai ETS for several reasons. First and foremost is the size and diversity of Shanghai and its industrial activities. Shanghai is one of the most important cities in China, as it is one of four provincial-level cities. Shanghai also has the largest GDP and urban population of all Chinese cities (China Statistical Bureau, 2018). Moreover, many of the sectors included in the Shanghai ETS are ubiquitous across China's industrial landscape: power utilities and steel and iron ore. Thus, findings from this study are not only of significant value to policymakers and residents in Shanghai, but can also be applied to similar industrial sectors across China.

Second, out of the seven pilot ETSs, Shanghai's market is one of the most consistent performers (see Table 1 for the policy design of the Shanghai ETS) (Zhou et al., 2020b). Zhou et al. (2020b) examined all seven ETS pilots in China from 2013 to 2015, and found that Shanghai was the only market to achieve 100% compliance. They

Table 1. Policy Design Features of the Shanghai ETS.

Design features	Details
Identifying potential participants	Firms are capped if they meet the following thresholds: (1) Emissions >20,000 tons CO_2 in 2010 or 2011 for major industrial sectors; the threshold is >10,000 tons CO_2 for non-industrial sectors. (2) Total 197 firms were capped during 2013–2015 and 368 firms were capped in 2016.
Cap coverage	Firms with mandatory targets cover industrial sectors such as the electricity generation sector, steel and iron, non-ferrous metals, paper, rubber, ferrous metals, chemicals, chemical fibre, petrochemicals, textiles, building materials, etc. Some entities are from non-industrial sectors such as aviation, ports, railway, large commercial shops and hotels, etc.
Scale	Share of the cap coverage in the total emissions: about 57%.
Covered emissions	Direct CO_2 emissions from industrial processes and energy consumption; indirect CO_2 emissions from heat and electricity consumption.
Cap setting and allowance allocation	Intensity-based emission caps are assigned to participating firms, which can then buy more emission allowance from the ETS market. Cap-setting is based on the historical emissions, or the sectoral benchmark and activity level. Emission allowance allocation: auctioning + free allocation.
Restriction on offset credit usage	≤5% of initial allowances.
Enforcing compliance	Non-compliance incurs a fine of 50,000–100,000 yuan; failure to submit the emission report incurs a fine of 10,000–30,000 yuan; failure to accept verification as required incurs a fine of 30,000–50,000 yuan.
Calendar	At the beginning of year T, the regulated firms receive their emission allowances for year T. The regulated firms must ask a third party to verify their reports and then submit the verified emission reports of year (T-1) by 30th April. At the end of June in year T, Shanghai ETS-regulated firms must submit the allowances valid during year (T-1) to comply with their targets of year (T-1).

Note: information collected from Swartz (2013), Wu et al. (2014), Wu et al. (2016), Zhang et al. (2017), and relevant Chinese policy documents (see Table S2).

also found that Shanghai ETS's trading volume and value are ranked middle among the seven pilots (Zhou et al., 2020b). In terms of policy features, the Shanghai ETS sets a 19% target reduction in carbon intensity, which is on par with the other ETS' targets of 17% to 21%. The sectors included in Shanghai's ETS account for around 57% of total CO_2 emissions. This is on the high side, as the shares of emissions range from 33% (Hubei) to 60% (Tianjin) (Zhou et al., 2020b). Like other ETSs, most initial CO_2 permits were allocated freely to firms, and a small portion were auctioned. Shanghai's policy on carbon credit offset is also the most conservative, as firms are only allowed to offset a maximum 5% of their CO_2 emissions using reductions from outside of Shanghai. In comparison, other ETSs allowed 10% (Zhou et al., 2020a).

Third, data limitations were a practical reason for our focus on Shanghai. Earlier studies evaluating China's ETS used annual emissions data aggregated at the provincial or provincial-sector level (Tang et al., 2020; Zhang et al., 2019a; Zhang et al., 2019b). While provincial-level data is more readily available, it may fail to deliver more nuanced evidence and policy insights. For this reason, we conducted our analyses at the weekly smokestack level. Although this approach limits the geographic scope of our study, it not only allows us to investigate how prices of CO_2 permits affect SO_2 emissions – thus elucidating a pathway mechanism – it also allows us to conduct heterogeneity analyses by sectors.

1.2. Literature review

This study is broadly related to two major strands of literature. The first strand comprises of studies examining the co-benefits of climate mitigation policies. In one of the earliest papers examining co-benefits in China, Jiang et al. (2013) used descriptive statistics to show that CO_2, SO_2, and particulate matter levels fell concurrently in the Tiexi district of Shenyang province following the implementation of stricter environmental regulations on energy usage and emissions standards. However, it is unclear from their analyses whether the emissions reductions were spurious or attributable to policy. Later studies attempted to provide evidence for stronger linkages between policy and co-benefits by using more rigorous modelling approaches. First, Cheng et al. (2015) projected the impacts of an ETS on SO_2 emissions in Guangzhou using a computational general equilibrium (CGE) model. Their model used the existing production levels, energy consumption, and emissions profiles of major industrial sectors in Guangzhou as well as trade and export statistics to predict the impact of an ETS on post-policy industrial output. They estimated that SO_2 emissions would be reduced by around 9% as a result of the ETS. Li et al. (2018) further incorporated a dose–response function of air pollution and health into their CGE model to estimate how projected air pollutant co-benefits would lead to health improvements. Across three hypothetical CO_2 emissions reduction policies in China, they found that health benefits from reductions in co-emitted pollutants would fully offset policy costs. Lastly, these simulated CGE models of co-benefits have also been applied outside of China. Using the same approach, Thompson et al. (2014) concluded that monetized health benefits from hypothetical nationwide GHG emissions reduction policies in the United States would offset at least 26% of policy costs. They also compared different policies and projected that an ETS would deliver the most co-benefits. A key similarity of all these studies is their use of ex-*ante* (as opposed to ex-*post*) models to examine the co-benefits of climate mitigation policies. This means that the data and policies examined in these studies are mostly simulated or hypothetical, and their findings are to a large extent determined by the models' assumptions.

The second strand of literature relates to those evaluating the effectiveness of the ETS in China. Due to the recent introduction of the ETS policies in China, this is a small but growing group of literature. A consensus on the ETS' effectiveness in reducing CO_2 emissions has emerged from the existing studies. One of the earliest empirical papers found that carbon emissions were reduced by around 1.7 tons/capita (Zhang et al., 2017). More recent studies using different methods and datasets similarly found that the ETS reduced carbon emissions by 10%-16% (Tang et al., 2020; Zhang et al., 2019a; Zhang et al., 2019b). However, a point of departure is that studies conducted at the sectoral level found no evidence of a reduction in carbon intensity (i.e. CO_2 emissions per production) as opposed to those conducted using provincial aggregate emissions. Specifically, Zhang et al. (2019a) found no statistical differences between the carbon intensity of sectors included under the ETS and those not covered by the ETS. In contrast, Zhang et al. (2019b) only used data from sectors included under the ETS and found differences in carbon intensity between ETS provinces and non-ETS provinces. One takeaway from these two studies is that different industrial sectors are likely to be affected in various ways by the ETS, and sector-level analyses can shed additional light on the effectiveness of the ETS.

In view of the existing studies on the co-benefits and effectiveness of China's ETS, our study makes the following contributions to the literature. First, and in contrast to studies based on ex-*ante* simulated models that currently dominate the literature on co-benefits, this is one of the first studies using actual emissions data. Moreover, we exploit the granularity of our dataset to include smokestack fixed-effects, which control for all time-invariant factors such as ownership, sector, location, scale of production, production technology, size of smokestacks, and management structure. All these factors are known to affect firms' pollution levels, and thus controlling for them will not only improve precision of the modelling, but also reduce confounding explanations.

Second, existing evaluations of ETS programmes in China and the EU have shown that different industrial sectors reduce their CO_2 emissions or CO_2 intensity in various ways (Borghesi et al., 2015; Tang et al., 2020; Zhang et al., 2019a; Zhang et al., 2019b). By extension, we should also expect to observe heterogeneous responses for co-benefits. However, co-benefit analyses at the sectoral level have yet to be attempted using actual emissions data. Findings from this study would thus provide more insightful policy guidance, as most ETS programmes are implemented at the sector level.

Lastly, the existing evaluation studies of ETS programmes have primarily relied on a reduced-form approach (e.g. Zhang et al. (2019a) used a difference-in-differences approach to estimate how the ETS affects CO_2 emissions). Such approaches, while empirically robust, are characterized as 'blackbox' applications, as they do not depict the mechanisms through which ETSs affect emissions (Deaton, 2010). For instance, firms could reduce their emissions purely due to the existence of a climate mitigation policy rather than reacting to specific policy lever(s), such as emissions permit price. In this study, we take a different empirical approach by directly using the ETS policy lever – prices of CO_2 emissions permits – to investigate their impact on SO_2 emissions, thereby furthering our understanding of how the ETS generates co-benefits in the form of reduced SO_2 emissions.

2. Method and data

In this section, we first propose an empirical model to estimate the relationship between Shanghai's ETS CO_2 prices and smokestacks' SO_2 emissions and discuss various robustness checks that we will run to rule out confounding explanations. Second, we introduce the dataset used in this study.

2.1. Empirical model

We focus on SO_2 in the empirical analysis as the primary co-benefit for two reasons. First, air pollution is one of the biggest environmental problems that China is facing, with SO_2 being a primary culprit (Gao et al., 2009; Li et al., 2016). Second, CO_2 is often emitted concurrently with SO_2, as they are both produced from coal combustion – the most commonly used fuel source across industry in China (Nam et al., 2013). As such, CO_2 emissions mitigation policies targeting industry in China, if effective, should also reduce SO_2 emissions.

A simple theoretical model of firm's emissions behaviours (see Supplementary Material (SM)) predicts that CO_2 emissions prices will have a negative relationship with SO_2 emissions, that is, as CO_2 prices rise SO_2 emissions will decline (along with CO_2 emissions). Here, we test this hypothesis by estimating the following fixed-effects panel regression model:

$$ln(SO_2)_{ijt} = \beta{*}(lnPrice_t) + \alpha_{ij} + W_t + f(t) + +\delta_t + u_{ijt} \tag{1}$$

$ln(SO_2)_{ijt}$ is the log-transformed SO_2 emissions from smokestack i of firm j at week t. The key explanatory variable, $lnPrice_t$, is the log-transformed weekly traded price of CO_2 emissions permits. The coefficient of interest is β, which can be interpreted as the elasticity of SO_2 emissions with respect to CO_2 prices (i.e. the percentage change in SO_2 emissions for a 1% change in CO_2 prices).

α_{ij} denotes the fixed effects of the smokestack, which controls for factors invariant to the smokestack, such as a firm's ownership and type, scale of production, and production patterns. W_t is a vector of location specific weather conditions such as temperature, wind speed, sea-level pressure and humidity, included up to a quadratic term. $f(t)$ is a quadratic time-trend to account for temporal changes in emissions over time. δ_t denotes time-fixed effects, included at monthly and yearly levels. These time-fixed effects are included to control for seasonal differences in emissions caused either by economic factors or by government policies. Lastly, u_{ijt} is the error term clustered at the smokestack level.

While we have taken care to rule out most confounding explanations by using an array of fixed effects, there are still several manners in which the results could be confounded. As such, we run three sets of robustness checks to rule out these alternative explanations. First, to ensure that our results are not confounded city- or regional-level factors that vary along with CO_2 prices, we use non-ETS firms from Shanghai and the nearby city of Ningbo as falsification tests. Second, we use lead CO_2 prices to rule out a reverse causality relationship with SO_2 emissions. Third, we relax several modelling assumptions to ensure that our baseline results are not driven by these empirical decisions: i) standard error clusters, ii) CO_2 prices at different time lags, and iii) aggregate the dataset to monthly level.

2.2. Data

The dataset used in this analysis ranged from March 2014 to December 2016 and is constructed from three sources. First, we obtained hourly SO_2 emission concentration (mg/m^3) at the smokestack level from a monitoring programme implemented by the Chinese Ministry of Ecology and Environment. The Ministry publicly identified major air, water, and soil pollution sources in each province across the entire country; once identified, these sources (mostly industrial factories, heating plants, and power stations) are required to install measurement devices at each emissions point. A 'snapshot' record of emissions for major pollutants is taken at each hour and automatically uploaded to a public server. In all, the data covers 103 smokestacks across 31 major air pollution sources in Shanghai. We use smokestacks rather than firms as the unit of analysis because smokestacks are the actual point sources of SO_2 emissions, and a firm may have multiple smokestacks. The hourly data is aggregated into weekly data to better suit our analytical approach. In all, this yielded 6,985 weekly observations of 103 smokestacks in 31 firms in Shanghai. To limit selection bias, the data sample includes most of the major air pollutant emitters in Shanghai. From the list of the major polluting firms in 2016, our sample covered 21 firms among the total 23 major air pollutant emitters in Shanghai.[6]

The second source of information is daily market price (CNY/ton CO_2) of CO_2 emission allowances from online sources that compile daily market data published by the exchanges of ETS markets in China.[7] Similarly, the daily prices are aggregated to the weekly level.

Lastly, Shanghai's weather data were collected from the China Meteorological Administration.

Table S1 displays the descriptive statistics (see SM). Shanghai's data consists of emissions measurements taken from 103 smokestacks, 96 of which are regulated by the ETS policy. The average weekly SO_2 emissions concentration is around 33.3 mg/m^3, and the average trading price is around 22.69 CNY/ton. Trading volume averages at around 50,000 ton of CO_2 per week.

3. Results

3.1. Relationship between Shanghai CO_2 prices and SO_2 emissions

The baseline results are shown in Table 2, in which fixed effects and covariates are incrementally added from Columns (1) to (3). We begin the estimation with a basic fixed-effects model. This specification includes smokestack and time fixed effects, which respectively control for firms' characteristics (such as sectors, production processes, ownership) and seasonal effects (such as the cost of raw materials and economy-wide factors). The coefficient for log-transformed CO_2 prices is −0.21, suggesting that SO_2 emissions will decrease by 0.21% for every 1% increase in CO_2 prices. Quadratic time trends and weather controls are incrementally added to the estimation models in Columns (2) and (3), respectively.

Table 2. Main regression model of CO_2 prices on SO_2 emissions.

VARIABLES	(1) Fixed effects	(2) +time trend	(3) +weather
ln(CO_2 price)	−0.213***	−0.124**	−0.126**
	(0.064)	(0.059)	(0.060)
Smokestack fixed effects	Yes	Yes	Yes
Year and month fixed effects	Yes	Yes	Yes
Week-year polynomial	No	Yes	Yes
Weather controls	No	No	Yes

Notes: N=6,738. Dependent variable is log-transformed weekly SO_2 emissions. Week-year polynomial are time trends included until the quadratic term. Weather controls are temperature, wind speed, sea-level pressure, windspeed, and precipitation. All weather controls are included until the quadratic term. Standard errors are clustered at smokestack level and shown in parentheses;
*** p<0.01, ** p<0.05, * p<0.1.

Our preferred specification is Column (3), in which all covariates and fixed effects are included. The coefficient for log-transformed CO_2 price is statistically significant at the 5% level, and estimated at around −0.13. This coefficient can be interpreted to indicate that a 1% increase in CO_2 price is associated with a 0.13% decrease in SO_2 emissions. These baseline results suggest that the Shanghai ETS, which effectively puts a price on CO_2, delivers co-benefits in the form of reduced SO_2 emissions.

Beyond this, we categorize ETS firms into two industrial sectors: i) power utilities (i.e. electricity and heat), and ii) non-power utilities (e.g. metals production and chemicals). Evidence from the EU shows that the CO_2 emissions of firms from sectors such as electricity are less affected by inclusion in an ETS (Martin et al., 2016). As such, we aim to examine whether there is similar heterogeneity in the Chinese context. A comparison between these two sectors reveals that SO_2 emissions from power utilities are less sensitive to CO_2 prices than firms from other industrial sectors (Table 3, Columns (1) and (2)). While the elasticity for power utilities is not statistically significant, firms in other industrial sectors present a different picture as the elasticity for CO_2 prices is around −0.2 and statistically significant at the 1% level.

As a follow-up, firms in the non-power utilities sector can be further distinguished into either ferrous metals or 'all other' industries (Table 3, Columns (3) and (4)). This is an important distinction in the context of China's industrial sectors, as the ferrous metals industry (consisting mainly of steel and iron factories) is not only a significant contributor to the economy, but also a major source of pollution (Guo et al., 2017; Yang et al., 2019). Moreover, due to overcapacity, the Chinese ferrous metal industry is known for low profit margins of around 1-10%, which are even negative in some cases (Tan-Soo et al., 2019; Xu & Liu, 2018). As such, this industry is likely to be more sensitive to production price changes. The results confirm our hypothesis, as SO_2 emissions from ferrous metals are highly sensitive to CO_2 prices with an elasticity of −0.3. In contrast, the coefficient for 'all other' industries is smaller at −0.14, and statistically significant at the 10% significance level.

Finally, we examine whether firms react differently to CO_2 prices over the course of a year. One possible reason that firms are more active during certain parts of the year is that firms in the Shanghai ETS have until June of the succeeding year to fulfil their emissions 'debts' or sell excess permits from the preceding year. As such, we divide each year into four quarters and estimate Equation (1) separately for Q1 (January to March) to Q2 (April to June) and Q3 (July to September) to Q4 (October to December). If firm managers pay

Table 3. Heterogeneity analyses by sectors and time periods.

VARIABLES	(1) Power utilities	(2) non-Power utilities	(3) Ferrous metals	(4) non-Ferrous metals	(5) Q1 & Q2	(6) Q3 & Q4
ln(CO_2 price)	−0.074	−0.206***	−0.293**	−0.135*	−0.289***	−0.070
	(0.084)	(0.067)	(0.116)	(0.073)	(0.105)	(0.074)
Observations	4,354	2,384	1,039	1,345	3,209	3,525

Notes: Dependent variable is log-transformed weekly SO_2 emissions. The non-Ferrous metals sector in Column (4) does not include power utilities firms. Q1 in Column (5) refers to the first quarter of the year, and so on. All models are estimated with smokestack-fixed effects, year- and month-fixed effects, week-year polynomial, and weather controls. Week-year polynomials are time trends included until the quadratic term. Weather controls are temperature, wind speed, sea-level pressure, windspeed, and precipitation. All weather controls are included until the quadratic term. Standard errors are clustered at smokestack level and shown in parentheses;
*** p<0.01, ** p<0.05, * p<0.1.

increased attention to their carbon emissions during the reporting period, then we would expect to see a larger response in Q1 and Q2 compared to other periods. We can see that firms' SO_2 emissions are only statistically correlated with CO_2 prices in the first and second quarter – the period in which they are required to fulfil emissions debts from the preceding year (Table 3, Columns (5)-(6)).

3.2. Robustness checks

The results thus far point to a negative association between CO_2 permit prices and firms' SO_2 emissions. While we have controlled for all time-invariant firms' characteristics and seasonal effects, the relationship observed thus far may be driven by confounding factors or the model selection. As such, we implement a series of robustness checks in this section to rule out these alternative explanations.

Here, we re-estimate Equation (1) using non-ETS firms in Shanghai. While these firms are also located in Shanghai, they are not subjected to ETS regulations. As such, we would not expect their emissions to be affected by CO_2 permit prices unless the earlier relationship we observed was confounded by Shanghai-wide time-varying conditions that are also correlated with emissions prices. Our estimation shows that non-ETS firms' emissions do not have any discernible relationships with CO_2 price, as the coefficients are not statistically significant (Table S2, Column (1)).

One limitation of the robustness check using non-ETS firms is that there are only seven smokestacks in the dataset that are not covered by the Shanghai ETS. As such, we conduct another falsification test by examining the influence of Shanghai CO_2 prices on the SO_2 emissions of industrial firms in the city of Ningbo (about 200 km from Shanghai in the neighbouring province of Zhejiang). While there are other cities that are geographically closer to Shanghai, Ningbo is arguably more similar to Shanghai in terms of GDP per capita, gross industrial output and SO_2 emissions, and geographical landscape (both are coastal cities). Since firms in Ningbo do not participate in Shanghai's ETS, any associations between their emissions and CO_2 prices would suggest that the results we observed earlier were driven by region-wide factors. As expected, the results show that Shanghai's CO_2 prices have no significant influence on the firms' SO_2 emissions in Ningbo (Table S2, Column (2)). Taken together, these two falsification checks allow us to rule out the explanation that baseline estimates were driven by confounding variables that are correlated with CO_2 prices.

We can also reason that there is a simultaneous relationship in which CO_2 prices are affected by firms' production decisions. For instance, firms may purchase more permits (thus driving up ETS prices) if they anticipate increased production. This is unlikely to be a source of concern here, as our analyses are conducted at the smokestack level, where any individual smokestack would not have sufficient market power to affect CO_2 prices. However, if this simultaneous relationship exists where firms collectively bid up CO_2 prices as they increase production (and thus SO_2 emissions), it would tend β in a positive direction and bias our findings downward. To test whether this simultaneous relationship exists, we estimate Equation (1) by using forward CO_2 prices. We can see in Figure S1 that there is no positive relationship between SO_2 emissions and forward or lead CO_2 prices, suggesting that reverse causality is unlikely (see SM).

We then also relax several modelling assumptions used in the baseline analysis. The results show that the standard errors are currently clustered at the smokestack level. Smokestacks are the obvious candidate, as weekly emissions are likely to be correlated over time for the same smokestack (Liang & Zeger, 1986). However, one could also reason that emissions over all smokestacks in any week are correlated. As such, we now cluster the standard errors by year-week. Table S2, Column (3) shows that statistical significance has not changed as a result (see SM).

In addition, we also use current-week CO_2 prices in the empirical analyses. However, it is also possible for firms to make production decisions based on the earlier CO_2 prices at which permits were purchased. To this end, we re-estimate Equation (1) by replacing CO_2 prices at time t with lagged prices from previous weeks (up until t-5 or five weeks before current). The coefficients are collected and plotted in Figure 1. We observe a decreasing trend in magnitude and statistical significance of the coefficients as prices are increasingly lagged. These results corroborate our baseline findings, as it is intuitive that production decisions in the current week are most affected by recent prices, with lagged prices having increasingly smaller influence. On the contrary, we would be concerned that the baseline results are spurious if a decreasing trend is not observed.[8]

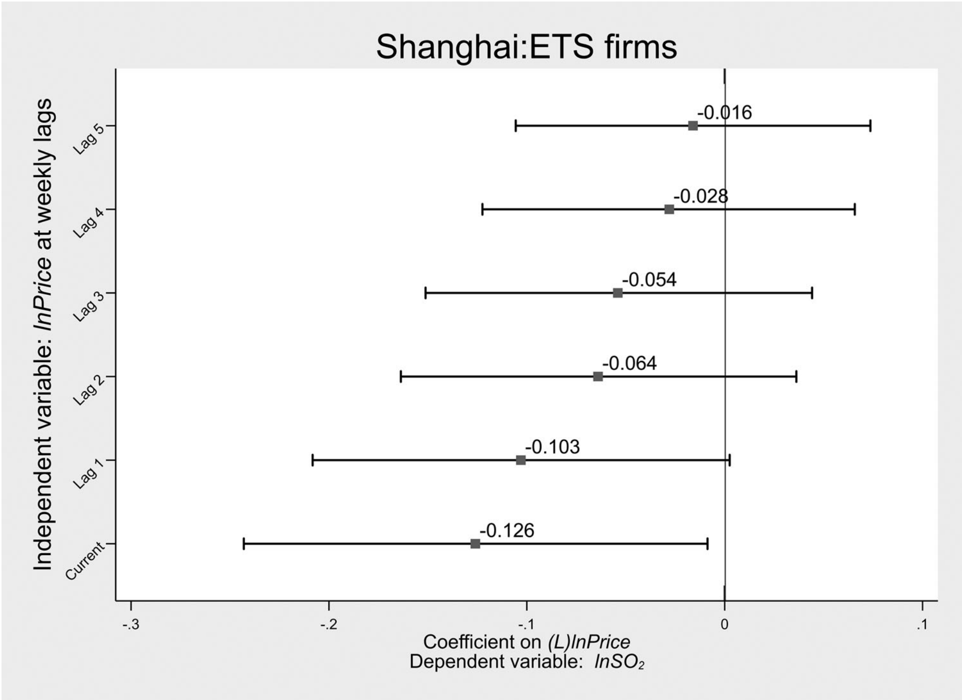

Figure 1. Association between current Shanghai CO_2 prices and ETS firms' SO_2 emissions at various lagged week.

Finally, the dataset is currently aggregated to the weekly level, however, it is also plausible that firms' managers make production decisions on a monthly basis. In this regard, we further aggregate the dataset to the monthly level so as to investigate whether the basic finding remains. Results in Table S2, Column (4) show that CO_2 prices still have a negative and statistically significant relationship with SO_2 emissions, indicating that the baseline results are not driven by the level of data aggregation (see SM).

4. Discussion and conclusions

4.1. Summary of findings

Like any price-based policy instrument, the purpose of an ETS is to increase firms' production costs by establishing a price for CO_2 emissions. Firms are expected to react to the costs by: 1) reducing production; 2) improving energy efficiency or using lower-CO_2 intensive energy sources; and/or 3) investing in less carbon-intensive plants or in technological innovations to reduce emission abatement costs in the long run. In turn, any of these actions are expected to lead to a decrease in CO_2 emissions and other co-emitted pollutants.

Recent studies evaluating China's ETS have found evidence of reduced CO_2 emissions (Tang et al., 2020; Zhang et al., 2017; Zhang et al., 2019a; Zhang et al., 2019b). In this study, we contribute a different and important dimension to the existing evidence base by investigating co-benefits: we apply ETS CO_2 prices to a high-frequency firm-level dataset of SO_2 emissions and arrive at the following findings.

First, we find that the elasticity of CO_2 permit price on SO_2 emissions is around −0.13 in Shanghai; a 1% increase in carbon price is associated with a 0.13% decrease in SO_2 emissions. These findings are supported by the inclusion of smokestack- and firm-fixed effects, and various time-trends that respectively control for any time-invariant firm characteristics and seasonal patterns. These baseline results hold under multiple falsification and robustness checks.

Second, compared to other industrial sectors, SO_2 emissions of electricity and heating plants are less sensitive to carbon prices. This is likely because electricity and heating plants provide essential and inelastic services;

thus, plant managers have lower flexibility to cut production and abate emissions. Another plausible explanation is that China had already implemented many policies to curb SO_2 emissions in the electricity and heating sector since the 1980s (Karplus et al., 2018; Yuan et al., 2013). Hence, these policies lessen the scope for co-benefits, as electricity and heating plants have already minimized their SO_2 emissions. While it was also found in the EU ETS that the electricity sector did not achieve a decrease in CO_2 emissions, this was likely for a different reason, as there is a high degree of price pass-through due to electricity spot markets (Abrell et al., 2011). That is, electricity plants in Europe sell their electricity supply to middlemen via auctions on a daily basis (Fabra & Reguant, 2014). In turn, due to the inelastic demand for electricity and the lack of electricity suppliers in many EU countries, most of the costs of CO_2 permits are passed on to consumers. In contrast, Chinese electricity tariffs are strictly regulated by the government, making price pass-through a less likely reason for the lack of reaction toward CO_2 prices.

Third, we also find that the relationship between CO_2 prices and SO_2 emissions is more apparent from January to June. One possible explanation for this is that Chinese ETSs are designed such that firms must fulfil past-year CO_2 emissions or sell excess permits by June of the next year, thus increasing their sensitivity toward CO_2 prices in the first two quarters.

4.2. Policy implications

Several research and policy implications arise from our findings. This is one of the first studies to use firm-level emissions data to demonstrate that GHG mitigation policy delivers co-benefits in terms of reduced SO_2 emissions. Our findings corroborate emerging evidence on China's ETS that carbon emissions are reduced by around 10-16% (Tang et al., 2020; Zhang et al., 2019a; Zhang et al., 2019b). In addition, we show that the ETS delivers additional societal benefits in terms of reduced SO_2 emissions. As we have quantified the price elasticity of SO_2 emissions, our research framework has applications beyond the ETS and can be used to predict co-benefits for other types of price instruments or policies, beyond the carbon tax.

Our findings also challenge the optimistic assumptions of previous studies, as we find that air quality co-benefits are highly nuanced and varied according to time, sector types, and policy design. Taken together with the first point, this implies that while the co-benefits of air quality improvement should be included in the cost–benefit accounting of climate mitigation policies, the magnitude of co-benefits is highly dependent on policy effectiveness, how policies are designed and implemented, and sectoral coverage. To use a recent example, power utilities are scheduled as the first sector to be included under China's nationwide ETS (NDRC, 2017). Our results show that policymakers should not expect significant co-benefits in air quality from this programme. However, our results suggest that extending the ETS (or other carbon pricing policies) to ferrous metal industries will have larger potential to deliver co-benefits.

Finally, China has launched several ambitious climate initiatives in recent years, with the newest being to achieve carbon neutrality by 2060 (Mallapaty, 2020). This is an especially challenging goal, as China is the world's largest GHG emitter. Moreover, preliminary estimates indicate that China will require around US$5 trillion worth of investments (or about 30% of its 2019 GDP) to achieve carbon neutrality. In this regard, policies such as the ETS are possible pathways to help attain carbon neutrality and policymakers should include co-benefits into the cost–benefit ledger to help justify costly capital outlays. Similarly, our findings and approach are not limited to Chinese settings, as policymakers worldwide also need to justify the cost of climate mitigation by demonstrating the benefits of their actions (Karlsson et al., 2020).

4.3. Research limitations

While our findings are consistent across a variety of robustness checks, this study has the following limitations. Due to data constraints, we only analyzed Shanghai, even though there are seven ETSs implemented across China. A richer dataset of firm-level emissions in other ETSs would allow future research to examine in greater detail how various policy features affect the effectiveness of such programmes. Additionally, while this is one of the first studies to use firm-level emissions to examine the effects of ETS, a more complete analysis could be conducted with additional information on firms' CO_2 trading behaviours. Lastly, China's ETS is still in a nascent stage and is only implemented in seven cities. Similar to other studies that examined the effectiveness of China's ETS, the results found here could be due to firms transferring production to non-ETS cities. This is especially true as many of the industrial firms included in the ETS operate in multiple cities across China.

Notes

1. For instance, suppose a city implements a carbon tax to reduce GHG emissions. The cost of administering the policy and the impact of the tax fall directly on the city's taxpayers and businesses. However, because GHG mitigation is a global public good (Tavoni et al., 2011), the benefits of abatement of global climate change are shared worldwide.
2. While there are many different types of co-benefits (e.g., biodiversity, economic growth, soil and water quality), existing studies have predominantly focused on co-benefits regarding air quality (Karlsson et al., 2020).
3. '*China's carbon trading scheme makes debut with 4.1 mln T in turnover*'. Source. Last accessed: Nov 15, 2021.
4. Global Carbon Atlas (http://www.globalcarbonatlas.org/en/CO2-emissions), last accessed: Oct 25, 2021.
5. U.S. Energy Information Administration international information (https://www.eia.gov/beta/international/data/browser), last accessed: Oct 25, 2021.
6. A list of major polluters can be found here: http://www.mee.gov.cn/gkml/hbb/bgt/201602/t20160204_329897.htm.
7. Online data sources are www.cneeex.com, www.chinatcx.com.cn, and www.tanpaifang.com.
8. There is a similar decreasing trend in coefficients even if we extend the number of lags to ten weeks. Results available upon request.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

Financial support from the National Natural Science Foundation of China (grant no #72134006, #71603267) and Singapore Ministry of Education - Singapore (start-up grant R603000237133) are gratefully acknowledged.

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