Do Chinese Provincial Emission Trading Schemes Reduce Emissions?

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Abstract

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This thesis answers the question of whether Chinese provincial emission trading schemes reduce emissions. I apply the generalized synthetic control approach to alleviate the non-parallel pretreatment trend problem of the differences-in-differences approach. The generalized synthetic control result shows that Chinese ETS pilots reduce 9.7% emissions, much less than the differences-in-difference result (32.3%) and previous literature estimates.

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Chapter 1

Introduction

In 2009, the State Council (2009) set a goal to reduce the nation's carbon emission intensity by 40% to 45% in 2020 compared with 2005, as was written as China's international commitment in the Paris Agreement in 2016. To reach the climate goal, the National Development and Reform Commission (2011) announced Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen as the pilots of carbon emission trading at the end of 2011. These seven regions started the emission trading schemes (ETS) in 2013 and 2014. Subsequently, Fujian started its carbon emission trading scheme in 2016. Most of these regions were previously selected as low-carbon development pilot areas which were to establish a low-carbon development plan in the local "Twelfth Five-Year Plan (2011-2015)" (National Development and Reform Commission, 2010). While ETS works on the market-based cap and trade principle to reduce emissions. China is an economy with a high-level of central government control, Therefore, observing positive allowance prices is not sufficient to prove that ETS is reducing emissions in China. This thesis explores the question: whether Chinese ETS pilots reduce emissions. If so, is it because pilot areas are going to reduce emissions anyway or a result of this market-based instrument?

The Ministry of Ecology and Environment (2019) stated that in 2018, the national carbon emission intensity decreased by 45.8% compared with 2005. This means China has met its international commitment in the Paris Agreement in advance. The Ministry of Ecology and Environment (2019) also stated that the ETS pilots were effective in reducing emissions. The empirical literature confirmed the statement (Hu et al., 2020; Chen and Xu, 2018). However, this thesis provides new evidence that the ETS pilots have not reduced emissions as much as estimates from the previous literature suggest.

This thesis employs two empirical approaches - Difference-in-Differences (DID) and Generalized Synthetic Control (GSC). The DID method compares the change in CO2 emissions between pilot and non-pilot provinces before and after pilots implemented. If there is some selection in choosing pilot provinces, DID produces biased estimates. One indicator of the existence of selection bias is the violation of parallel pretreatment trend. To relax the parallel pretreatment trend assumption required by DID, I employed the GSC method to predict the counterfactual CO2 emissions for pilot provinces.

Here are my findings: The aggregate DID analysis indicates that the Chinese ETS pilots reduce 32.3% emissions (statistically significant at the 1% significance level). While using GSC to alleviate the selection bias problem of DID and get a better counterfactual of pilots, ETS only reduces 9.7% emissions (not statistically significant at the 10% significance level). To get closer to the emissions covered by ETS, test the effectiveness of ETS under different levels of strictness, and distinguish ETS from other policies, I conduct sectoral analysis in electricity, heating, and manufacturing sectors. The sectoral analysis tells a similar story as the aggregate analysis. The expectation effect analysis shows no evidence of an expectation effect. The mechanism analysis indicates that ETS reduces emissions in the electricity sector via adjusting energy structure (increasing natural gas consumption and decreasing coal consumption) and decreasing energy consumption, the heating sector via adjusting energy structure, and the manufacturing sector via decreasing energy consumption. The heterogeneous effect analysis indicates that while choosing higher economic liberalization provinces instead of all provinces as the sample, the emission reduction effect of ETS is small. This is consistent with the GSC results because higher economic liberalization provinces construct a more appropriate control group than all provinces.

This thesis builds on the current literature in several ways. (1) The data employed in this paper includes 10 more years of data than previous literature. This enhances my ability to test the pre-pilot trend assumption. (2) The data in this paper can separate the heating and electricity sectors, while previous literature cannot.

This feature allows to distinguish the effect of ETS from other policies. (3) This thesis compares the results from DID and GSC to show the idea that the choice of pilot provinces results in the different pre-pilot trend between the pilot and non-pilot groups and GSC predicts a better counterfactual group than the non-pilot group. (4) This thesis examines the reasons of heterogeneous effects by sector via the design of ETS pilots, while previous literature does not dig into detailed designs and link to the effect of ETS.

The rest of this thesis is organized as follows: the next section provides some background, both theoretical and empirical. Next, I provide an overview of China's ETS Pilots. I then describe my empirical methods, data, and results. Finally, I carry out robustness checks, and conclude.

Chapter 2

Background

2.1 Theoretical Background

There are two market-based instruments to regulate pollution: carbon tax and cap and trade. Pigou (1924) argued that taxing the pollution at its social marginal damages would equate private and social marginal costs and ensure an efficient market outcome. Coase (1960) argued that private bargaining under low transaction costs along with clear property rights can substitute for government regulation. A cap-and-trade program implements the Coase Theorem under climate change, where government sets the total number of permits (the right to pollute) and allocates permits. While a carbon tax puts a price on pollution and let the market determine the amount of pollution, a cap-and-trade system puts a cap on pollution and lets the market determine the price of the pollution right.

A main attraction of market-based instruments is to reduce emissions at the lowest possible cost. However, there is much debate between a carbon tax and a cap-and-trade system as a better reaction to climate change. A carbon tax is preferred in the sense that it is difficult to identify the individuals suffering the damages from pollution and the transaction costs are high given the number of people affected (Metcalf, 2019); A cap-and-trade system is preferred in the sense that it provides more certainty regarding emissions levels and is easier to accommodate with other countries' carbon mitigation programs (Stavins, 2008).

From the perspective of efficiency, the preference between price and quantity depends on the relationship between marginal cost and marginal benefit. Weitzman

(1974) maintained that cost uncertainty matters with the identity of efficient instrument depending upon the relative slopes of the marginal benefit and cost functions. Stavins (1996) argued that both cost uncertainty and benefit uncertainty affect the choice of efficient instrument.

As for global warming, the danger depends more on the stock of greenhouse gases than the flow. Staring (1995) proposes the open-loop dynamic model to compare taxes and quotas for a stock pollutant. Hoel and Karp (2001) extended the model from the asymmetric information on the intercept of the marginal abatement costs to the slope, or say, from additive uncertainty to multiplicative uncertainty. Under both circumstances, taxes dominate quotas.

2.2 Empirical Background

2.2.1 European Union Emissions Trading System

There are 11 countries and regions[1] that have implemented carbon-trading initiatives (World Bank, 2019). Among them, the European Union Emission Trading System (EU ETS) is the largest program, covering around 45% of the EU's greenhouse gas emissions (European Commission, 2020a).

Ellerman and Buchner (2008) is one of the first attempts to estimate the abatement of EU ETS. Comparing installation-level emissions in the first trading year (2005) to baseline emissions data in around 2002 reported in National Allocation Plans (NAPs), they concluded that the emissions were reduced by 3.4% for EU23 countries in 2005. Then they estimated the range of the growth rate in business-as-usual (BAU) emissions taking into account real GDP growth and carbon intensity growth to project the baseline emissions in 2002 to the BAU emissions in 2005 and concluded that emissions were reduced by 7% to 10% in 2005. This estimate is greater than that of Ellerman and Buchner (2008). One possible reason is that the baseline emissions data suffer from potential bias problem because emissions data, the basis for future allowance allocation, were provided by firms.

[1] Subnational: Canada (Alberta 2007, Quebec 2013, British Columbia 2016), United States (RGGI States 2009, California 2012, Washington 2017), Japan (Tokyo 2010, Saitama 2011), China(Beijing Guangdong Shanghai Tianjin Shenzhen 2013, Chongqing Hubei 2014, Fujian 2016); National: New Zealand 2008, Switzerland 2008, Kazakhstan 2013, Korea 2015, Australia 2016, Canada 2019; Regional: EU plus Norway, Ice land and Liechtenstein 2005.

Rather than using a single baseline emission point, Anderson and Di Maria (2011) obtained historical emissions data for EU25 countries from Eurostat and matched to the sectors participating in the EU ETS. Controlling for industry economic activity levels, weather and energy prices, they used a dynamic panel approach - bias corrected least squared dummy variable estimation - to estimate the country-level BAU emissions of the first pilot phase (2005-2007). They found that verified emissions were 2.8% lower than BAU emissions.

Instead of country-level panel data, Abrell et al. (2011) obtained emissions and allowances data of 2101 firms (3608 installations) over 2005-2008 from the European Commission (Community Independent Transaction Log, CITL) and performance data over 2003-2008 from the Amadeus database. They applied the differences-in-differences method to capture the change of emissions reduction from the first to the second phase and found the 2007-2008 emissions reduction was 3.6% larger than the 2005-2006 reduction.

2.2.2 Chinese Provincial Emission Trading Schemes

Due to the fact that all EU member states participate in EU ETS, there is no control group for EU ETS to conduct difference-in-difference or synthetic control methods. EU ETS related literature estimates the counterfactual emissions for EU member states. In contrast, only a part of Chinese provinces are pilot areas, which allows the application of difference-in-difference and synthetic control methods.

The paper by Hu et al. (2020) is closest in spirit to this paper. Based on provincial industry-level data from 2005 to 2015, Hu et al. (2019) adopted a difference-in-difference approach and set 2011 as the treatment timing. They found that ETS decreases energy consumption of the regulated industries by 22.8% and CO2 emissions by 15.5%. They added leads and lags in the model to investigate the expectation effect of ETS and found a two-year lagging effect of energy consumption and non-lagging effect of emission. Channel analysis indicates that the policy effects are mainly driven by improving energy technical efficiency and adjusting industrial structure. Heterogeneous analysis shows that ETS performs better in areas with high levels of environmental enforcement and marketization.

Using provincial industry-level data from 2005 to 2016, Zhang et al. (2019) employed the Generalized Synthetic Control method to evaluate the carbon emission intensity inhibition of the ETS in six provincial pilots and pilot industries covered by ETS. They find that ETS reduced carbon emission intensity significantly only in Beijing and Guangdong. Through industry analysis with respect to Beijing and Chongqing, the results of the production and supply of electric power, steam and hot water, petroleum processing and coking in Beijing have a significant impact on the ETS. Only the smelting and pressing of ferrous metals in Chongqing has a significant impact on the ETS.

Chen and Xu (2018) use the synthetic control method to evaluate the carbon mitigation effect of ETS in Hubei, Guangdong (including Shenzhen), and Tianjin since they cannot get good pre-policy synthetic results for Beijing, Chongqing, and Shanghai. The emissions data is aggregate at province level from 1995 to 2015. The results show that Hubei reduced emissions by 59.5 million tons in 2015, and Guangdong reduced emissions by 37.1 million tons in 2015. The results in these two pilots support the expectation that more trading volume results in more emissions reduction.

This paper contributes by: (1) I collected sectoral energy consumption data at province level over the period of 1995 to 2017. In this way, this paper has ten more years of data comparing to previous literature with sectoral data (Hu et al., 2020) and (Zhang et al., 2019). Also, this paper has sectoral data comparing to previous literature with data from 1995 to 2015 (Chen and Xu, 2018) (2) The data I collected can separate the heating and electricity sectors, while Hu et al. (2020) and Zhang et al. (2019) cannot. This feature enables me to distinguish the effect of ETS from the Air Pollution Control Action Plan. (3) This paper compares the results from DID and GSC to show the ideas that the choice of pilot provinces results in the different pre-pilot trend between the pilot and non-pilot groups and GSC predicts a better counterfactual group than the non-pilot group. (4) This paper understands the reasons of heterogeneous effects by sector via the design of ETS pilots, while previous literature does not dig into detailed designs and link to the effect of ETS.

Chapter 3

Overview of China's ETS Pilots

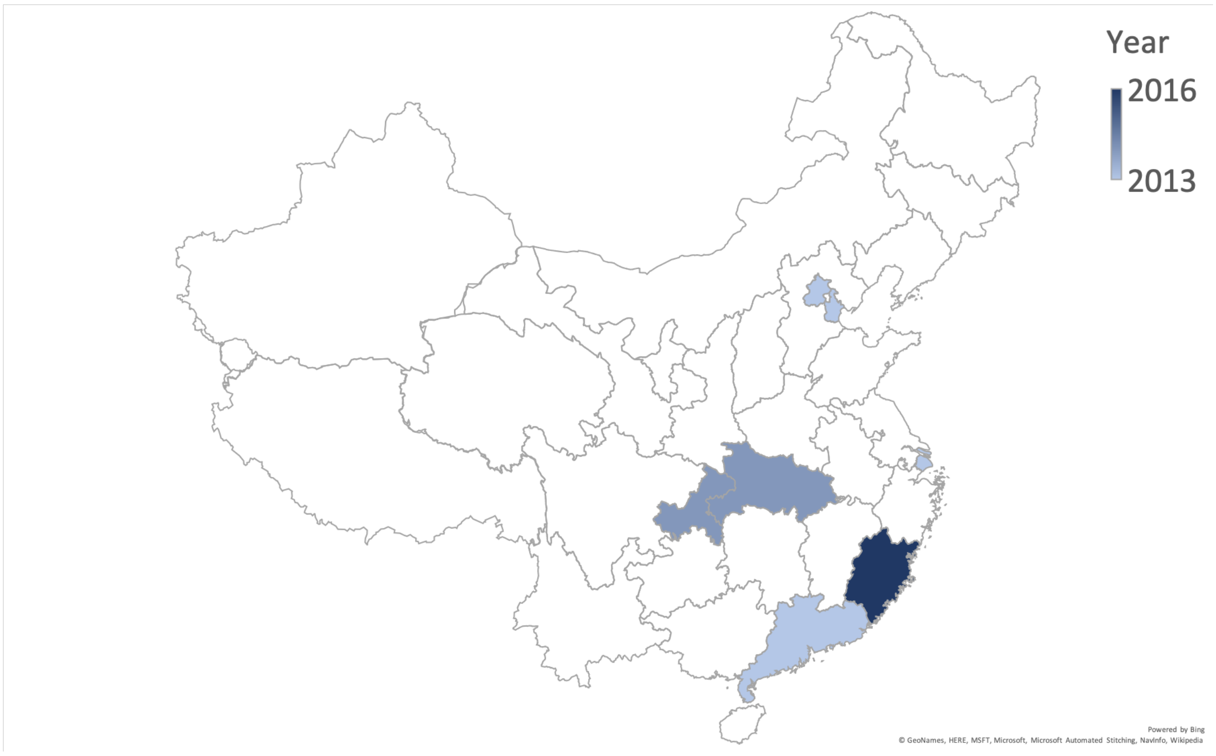
3.1 Policy Overview

At the end of 2011, the National Development and Reform Commission (2011) announced Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen as the pilots of carbon emission trading. After two-year preparation, these pilots started the emission trading scheme in 2013 and 2014. Subsequently, Fujian started its carbon emission trading scheme in 2016.The cap-and-trade system is a key instrument for the province to transform and upgrade its economy, increase welfare and raise awareness of GHG emission control among society and businesses. As shown in Figure 3.1, these pilots are distributed in central and eastern China, which is relatively more developed. Most of them (Guangdong, Hubei, Tianjin, Chongqing, Shenzhen) were previously selected as low-carbon development pilot areas in 2010 (National Development and Reform Commission, 2010). These pilot areas have to establish a low-carbon development plan in the local "Twelfth Five-Year Plan (2010-2015)".

Designs of different ETS pilots vary widely, I summarize the key features and compare them with those of EU ETS in Table 3.2.

Among all pilots, the Chongqing pilot is the only one that covers non-CO_2 greenhouse gases. Guangdong is the highest GHG emissions pilot and has the highest emission coverage 422 MtCO_2e. Shenzhen - the special economic zone in Guangdong - is the lowest GHG emissions pilot and has the lowest emission coverage 31 MtCO_2e. Hubei has the lowest coverage before changing the threshold of covered firms to 10,000 ton tce.

FIGURE 3.1: Chinese Provincial ETS Distribution



As for covered sectors, all Chinese pilots cover the electricity and manufacturing sectors. All northern pilots cover the heating sector. Only the Tianjin pilot covers the mining and quarrying sector. One possible reason is to account for emissions associated with the offshore Bohai Bay oil and gas development. The Beijing, Fujian, Guangdong, and Shanghai pilots cover the transport sector. The Beijing, Shenzhen, Shanghai, and Tianjin pilots cover public buildings. Public buildings consume electricity, which is the source of indirect emissions. This indicates one feature of China's ETS: double counting[1], that is, cover both direct and indirect emissions[2]. It helps cut emissions in two ways. First, China's electricity price is regulated, which means

[1] According to the US Environmental Protection Agency, direct emissions include on-site fossil fuel combustion and fleet fuel consumption and indirect emissions result from the generation of electricity, heat or steam purchased by the Agency from a utility provider.

[2] If the electricity is imported from outside the pilot region, the related emission is not double counted.

that the cost increased by ETS cannot be passed to consumers by increasing electricity price. By permit price payment, double counting increases consumers' electricity consumption cost to incentivize them to reduce electricity consumption (specifically, consumers are large buildings) and to prohibit downstream energy consumers from replacing fossil fuel consumption with electricity consumption (for example, consumers are petrochemical firms). Second, covering indirect emissions associated with imported electricity alleviates carbon leakage by increasing imported electricity consumption cost. More detailed industries covered by ETS can be found in Table 3.3.

The share of GHG emissions covered, covered sectors, threshold, and number of covered firms could reflect the ambition of the pilot to reduce emissions. Overall, the Beijing and Shenzhen pilots have the greatest number of firms and covered sectors (see Table 3.2 and 3.3).

As for cap setting approach, the Chongqing pilot is different from all other pilots. The 2013 cap for Chongqing is 125,197,019 ton CO_2e (about 40% of total GHG emissions), which is the sum of the highest emissions in 2008-2012 for all covered firms. The plan is: before 2015, the cap reduces 4.13% annually; after 2015 the cap reduction rate is set based on the carbon reduction goal set by the central government[3]. Then, firms in Chongqing have to report their annual emissions. if the sum of reported annual emissions is less than the total cap, the annual allowance for each firm is its reported emissions. If the firm's reported annual emissions is greater than the highest historical emissions, the allocation base is the average of the reported emissions and the highest historical emissions; if the firm's reported annual emissions is less than the highest historical emissions, the allocation base is the reported emissions. If the sum of allocation base across firms is less than the total cap, the annual allowance for each firm is the allocation base; if the sum of allocation base across firms is greater than the total cap, the annual allowance for each firm is determined by the weight of its allocation base. Under this allocation rule, covered firms have incentive to over report annual emissions.

[3]The rate after 2015 was set as 4.85% annually later. In fact, the cap doesn't reduce exactly as planned. For example, the cap in 2014 is 115,686,722 ton CO_2e, 7.6% less than that in 2013.

TABLE 3.1: Control Coefficients by Industry in Beijing Pilot

Industry	2013	2014	2015	2016	2017	2018
Cement	0.980	0.960	0.940	0.900	0.800	0.715
Petrochemical	0.980	0.960	0.940	0.920	0.830	0.800
Other manufacturing	0.980	0.960	0.940	0.920	0.900	0.870
Service	0.990	0.970	0.960	0.960	0.960	0.960
Gas installation in heating industry	1.000	1.000	1.000	1.000	1.000	1.000
Coal installation in heating industry	0.998	0.995	0.990	0.985	0.980	0.970
Gas installation in electricity industry	1.000	1.000	1.000	0.990	standard	standard
Coal installation in electricity industry	0.999	0.997	0.995	0.980	standard	standard
Mobile installation in transportation industry	-	-	0.995	0.995	0.995	0.980

Source: Beijing Environment Exchange (2020)

Apart from Chongqing, all other pilots employ grandfathering and benchmarking to determine the firm-level cap and do not set a total cap. This approach is known as the bottom-up rule. Grandfathering sets the annual allowances as a proportion of the base-year annual emissions or as the product of the annual output produced or input consumed and a proportion of the base-year carbon intensity. The proportion is named as control coefficient. Benchmarking sets a standard of performance, representing the emissions associated with each unit of activity.

Take Beijing as an example; allowances for each firm consist of three parts: allowances for incumbent installations, allowances for new installations, and allowances for adjustments. (1) For incumbent installations, grandfathering based on historical emissions is adopted in the stationary installations in the cement, petrochemical, and other manufacturing industries, transportation, and service sector; grandfathering based on historical carbon intensity is adopted in the electricity sector and the mobile installations in transportation sector. Starting from 2017, benchmarking (emissions per activity - MHh or GJ) is adopted for all installations in the electricity sector. The control coefficients and emission standards for Beijing are presented in Table 3.1. Firms in the manufacturing industry experienced the strictest regulation; firms in the heating industry and transportation industry experienced the most lenient regulation. Without considering the change of annual output and base-year emissions[4], in 2018, manufacturing firms can emit 45.5%-63% of 2009-2012; service firms can emit 81.6% of 2009-2012; coal installations in heating industry can emit 92% of 2009-2012; mobile installations in transportation industry can emit 96.5% of 2009-2012; gas installations in heating industry can emit the same the same level as

[4]The historical base year for stationary installations is 2009-2012 since 2013. The historical base year for mobile installations changed from 2009-2012 to 2013-2016 in 2018.

2009-2012. The fact that the restriction in gas installations in more lenient than that in coal installations is to incentivize firms to switch from the dirty energy - coal - to the clean energy - gas. Starting from 2017, all installations in electricity industry are subject to the same emission standard, so it is hard to tell how much of 2009-2012 can be emitted. (2) New installations are subject to the emission standards (per activity - output or area). (3) Allowances are deducted by the same proportion as the emissions if the annual emissions reduce by more than 20% or the annual carbon intensity reduce by more than 50%. But allowances won't be less than the amount of emissions last year.

As for allowance allocation, all allowances in Chongqing are freely allocated. Allowances in other pilots are granted freely or auctioned off. The proportion of allowances that are auctioned off is usually below 10%. The local government also reserves a small proportion (reservation + auction $<10\%$) of allowances to adjust the market when market price is highly volatile.

Trading approaches are the same across pilots: public trading and agreement transfer. The implementing details may vary by pilot. For example, public trading in Beijing has three forms: overall transaction, partial transaction, and fixed price transaction. Under the overall transaction method, only one responding party and the declaring party can conclude a transaction. The number of allowances declared in the transaction has to be completed once. Under the partial transaction mode, one or more responding parties may conclude a transaction with the declaring party and partial transactions are allowed. Under the pricing transaction method, one or more responding parties and the declaring party can use the declared price of the reporting party. Partial transactions are allowed. Public trading in Beijing allows both buy declaration and sell declaration; public trading in Tianjin only allows overall transaction and sell declaration, which is more like the standard auction.

All pilots allow the use of China Certified Emission Reductions (CCERs)[5]. The maximum amount of CCERs allowed to use varies by pilot, as shown in the row "Offset ratio" of Table 3.2. Fujian also has provincial certified emission reductions

[5]According to the Interim Measures for the Management of Voluntary Greenhouse Gas Emission Reduction Transactions of the National Development and Reform Department, CCER is the emission reduction of voluntary emission reduction projects that have been filed and registered in the national registration system

(FFCERs).

All pilots adopt the Monitoring, Reporting & Verification (MRV) regulation. Covered firms which do not submit emissions report or not submit enough allowance by the compliance date will be fined.

3.2 Contrast to EU ETS

The main differences between the EU ETS and Chinese ETS are covered sectors, covered unit, cap setting, allowance allocation, and trading approach.

The EU ETS shares similar sectors and coverage ratio as the Chinese ETS pilots. However, the EU ETS does not cover oil and gas exploration (as Tianjin), public transportation (as Beijing), and large buildings (as Beijing, Shenzhen, Shanghai, and Tianjin). As mentioned in previous section, the coverage of large buildings indicates the double counting feature of the Chinese ETS.

The covered unit for the EU ETS is the installation, while the covered unit for the Chinese ETS pilots is the firm. Therefore, the threshold to be covered by ETS is different between EU and Chinese pilots, as shown in Table 3.2. The covered emissions also differ. While EU ETS only covers direct emissions from installations (stationary and mobile)[6], emissions from firms include both direct and indirect emissions.

As for cap setting, EU ETS shares the same approach as the Chongqing pilot. The 2013 cap for EU ETS from fixed installations was set at 2,084,301,856 ton CO_2e (about 45% of total GHG emissions)(European Commission, 2020a). During phase 3 (2013-2020), this cap decreases each year by a linear reduction factor of 1.74% of the average total quantity of allowances issued annually in 2008-2012. This amounts to a reduction of 38,264,246 allowances each year. The linear reduction factor was set in line with the EU-wide climate action targets for 2020 - the EU ETS sector-specific 21% emissions reduction target relative to 2005. The total amount of allocation each installation should receive is determined by product-related GDG emission benchmarks, which are set at the average emission level of the 10% most efficient installations with each sector (European Commission, 2020b). As mentioned in previous

[6]European Commission (2020b) states that indirect emissions from electricity consumption are not covered under the EU ETS and do not need to be reported.

section, the Chinese ETS pilots other than Chongqing adopted the bottom-up rule to set the firm-level cap.

For the EU ETS phase 3, the power generation sector is subject to 100% auctioning. Industrial (non-power) and heating sectors receive free allocation for a transitional period. In 2013, 80% of the quantity determined by the free allocation rules for the industrial sector will be allocated for free, decreasing to 30% in 2020, with a view of 0% in 2027[7] (European Commission, 2020b).

As for trading, the EU ETS trading market shares similar features as the Chinese ETS pilot trading markets. EU ETS trading can be done through "Over-the-Counter" (OTC) (directly between buyers and sellers), exchanges or auctions. OTC is similar to agreement transfer; exchanges and auctions are similar to public trading. The EU ETS trading units include EUA (EU Allowance), EUAA (EU Aviation Allowances), CER (Certified Emission Reduction), and ERU (Emission Reduction Unit). Similar to the Chinese pilots[8], for transactions through exchanges, the EU ETS allows spot and futures transactions; for OTC transactions, EU ETS allows spot and forwards[9] transactions. Different from the Chinese pilots, options and swaps (exchange one security for another, e.g., EUA to CER) can take place in the EU ETS.

Both the Chinese ETS pilots and EU ETS adopt the Monitoring, Reporting & Verification (MRV) procedure. In phase 3, participants who fail to surrender allowances by the compliance date are fined 100 Euro per tCO2, adjusted with the EU inflation rate from 2013 onwards, for which they fail to submit an allowance. Furthermore, the shortfall in compliance will be added to the compliance target of the following year (European Commission, 2020b). In China, participants who fail to surrender allowances by the compliance date are fined about three times of market average price per tCO2 for which they fail to submit an allowance. But the shortfall in compliance will not be added to the next year.

[7]Any sector that it is deemed to face a significant risk of carbon leakage from exposure to non-EU competition due to price on CO2, will continue to receive up to 100% of the quantity determined by the free allocation rules for free throughout the entirety of phase 3.

[8]Shanghai and Hubei allow futures contracts.

[9]Forwards are different from a futures contract in that they are non-standardized and take place OTC, rather than via an exchange.

TABLE 3.2: ETS Design Features

	Beijing	Chongqing	Fujian	Guangdong	Shenzhen	Hubei	Shanghai	Tianjin	EU ETS
Trading starting date	11/28/13	6/19/14	12/22/16	12/19/13	6/18/13	4/12/14	11/26/13	12/26/13	01/01/2005
Covered GHG	CO2	CO2, CH4, N2O, HFC, PFC, SF6	CO2	CO2	CO2	CO2	CO2	CO2	CO2, N2O, PFC
Total GHG emissions (2012, MtCO2e)	188	243	333	611	153	463	298	215	4750
Share of GHG emissions covered (2018)	45%	40%	60%	60%	40%	55% (35% before 2017)	57%	55%	45%
Coverage (2018, MtCO2e)	85, (50 before 2015)	100	200	422	31	256 (162 before 2017)	158	160	1855
Covered sectors	Electricity, heating, manufacturing, transport (added in 2015), large building	Electricity, heating, manufacturing	Electricity, manufacturing, transport	Electricity, manufacturing, transport (added in 2016)	Electricity, manufacturing, large buildings	Electricity, heating, manufacturing	Electricity, heating, manufacturing, transport, large building	Electricity, heating, mining and quarrying, manufacturing, large building	Electricity, heating, manufacturing, transport
Threshold (ton CO2e)	10,000 (2009-2012), changed to 5,000 in 2015	20,000 (2008-2012)	10,000 ton tce (2013-2015)	20,000 (2011-2012) or 10,000 ton tce	Industry 3,000, large building 10,000 m2	60,000 ton tce (2010-2011), changed to 10.000 ton tce in 2017 (2014-2016)	Industry 20,000, non-industry 10,000 (2010-2011)	20,000 (2009 onwards)	20MW thermal rated input
No. of units (2014)	415, added 430 firms in 2015	254	277	242	635 firms + 200 large buildings	138, 344 in 2017	191	114	11000
Free allocation	Yearly	Yearly	Yearly	Yearly	Every three years	Yearly	Every three years	Yearly	Yearly
Allocation approach	Grandfather and benchmark	Cap setting and unit report	Grandfather and benchmark	Grandfather and benchmark	Benchmark	Grandfather and benchmark	Grandfather and benchmark	Grandfather and benchmark	Cap setting
Paid allocation	5% of annual quota is reserved for auction	None (before 2015)	10% of annual quota is reserved	quarterly auction (3% of annual quota)	3% of annual quota is reserved for auction (before compliance date)	3% of annual quota is reserved for auction	when appropriate (before compliance date)	with a high volatility of market price	auction: electricity, and part of other industries and aviation
Trading participant	covered firms, institutions and individual investors	covered firms, institutions and individual investors	covered firms, institutions and individual investors	covered firms, institutions and individual investors	covered firms, institutions and individual investors	covered firms, institutions and individual investors	covered firms, institutions	covered firms, institutions and individual investors	Anyone with an account in the EU registry
Trading approach	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	public trading and agreement transfer	Over-the-Counter, through exchanges or via auctions
Limit of fluctuation	public trading 20%	20%	None	10%	10% (big deal 30%)	10%	30%	10%	
Trading unit	BEA, CCER, verified carbon sink and energy conservation	CQEA, CCER	FJEA, CCER, FFCER	GDEA, CCER	SZA, CCER	HBEA, CCER	SHEA, CCER	TJEA, CCER	EUA, EUAA, CER, ERU
Offset ratio	<= 5% of allocation	<=8% of emissions	FFCER<=10% of emissions CCER<=5% of emissions	<= 10% of emissions in last year	<=10% of emissions	<= 10% of allocation	<= 5% of allocation	<=10% of emissions	
Offset region	Local projects >=97.5%	No restriction	All local projects	Local projects >=70%	No restriction	All local projects	No restriction	No restriction	
Emission report	20-Mar	20-Feb	28-Feb	15-Mar	31-Mar	28-Feb	31-Mar	30-Apr	31-Mar
Verification report	5-Apr	20-Apr	-	30-Apr	30-Apr	30-Apr	30-Apr	30-Apr	31-Mar
Compliance Date	15-Jun	20-Jun	28-Jun	20-Jun	30-Jun	30-Jun	1-Jun	31-May	30-Apr
Penalty for non-compliance	3-5 times of market average price	3 times of market average price	1-3 times of market average price (<30 thousand yuan),	double deduction next year, 50 thousand yuan	deduction next year, 3 times of market average price	1-3 times of market average price (<150 thousand yuan), double deduction next year	50-100 thousand yuan	Correct by a deadline, 3 years without discount policy	100 Euro/tCO2, and added to the compliance target of the following year.
Other penalty (thousand yuan)	<50 if not submit reports by deadline	20-50 if no report, 30-50 if fake report	10-30 if not submit reports by deadline	10-20 if no report	50-100	10-30 if no report, 150 if violate transaction rule	Record in credit history, cancel fund support	Correct by a deadline	Vary by member states
No. of verification agency	22, 35 (2015 onwards)	11	15	16	21	1	10	4	

Total GHG emissions, share of emissions covered, and cap data source: World Bank (2020). ***shenzhen is strange because 153*40%=60 not 31***
Other source: Beijing Environment Exchange (2020), Chongqing Environment Exchange (2020),Fujian Environment Exchange (2020),Guangdong Environment Exchange (2020),Hubei Environment Exchange (2020),Shanghai Environment Exchange (2020),Shenzhen Environment Exchange (2020),Tianjin Environment Exchange (2020),(European Commission, 2020b).

TABLE 3.3: ETS Covered Sectors

	Beijing	Chongqing	Fujian	Guangdong	Shenzhen	Hubei	Shanghai	Tianjin	EU
Thermal Power	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity
Heating Supply	Heating	Heating				Heating	Heating	Heating	Heating
Mining and Quarrying								Oil and gas exploration	
Manufacturing	Petrochemical, food and beverage, cement, etc	Petrochemical, cement, paper, non-ferrous, steel, etc	Petrochemical, chemical, steel, nonferrous, paper, ceramics, building materials,	Petrochemical, steel, cement, ceramic, paper (added in 2016)	Manufacturing	Metallurgy, petrochemical, chemical, steel, cement, non-ferrous, automobile, paper, medicine and pharmacy, food and beverage, etc	Steel, petrochemical, chemical, non-ferrous, building materials, textile, paper, rubber, chemical fiber	Steel, petrochemical, chemical, etc.	Oil refineries Coke ovens Steel plants Cement clinker Glass Lime Bricks Ceramics Pulp Paper and board Aluminum (from 2013) Petrochemical (from 2013)
Transport, Storage and Post	Public transportation (added in 2015)		Aviation	Aviation (added in 2016)			Aviation, railway		Aviation (from 2012)
Wholesale, Retail Trade and Hotel, Restaurants & Other	Large buildings (hospital, university, etc)				Large buildings		Airports, ports, Large buildings	Large buildings	

Coal Washing & Coking & Briquettes, Farming, Forestry, Animal Husbandry, Fishery, Construction, and Residential Consumption are not covered by any pilots.
Source: Beijing Environment Exchange (2020), Chongqing Environment Exchange (2020),Fujian Environment Exchange (2020),Guangdong Environment Exchange (2020),Hubei Environment Exchange (2020),Shanghai Environment Exchange (2020),Shenzhen Environment Exchange (2020),Tianjin Environment Exchange (2020),(European Commission, 2020b).

Chapter 4

Empirical Methods

This paper employs two empirical methods - Difference-in-Differences (DID) and Generalized Synthetic Control (GSC) - to test whether ETS reduces emissions in Chinese pilots. The idea of DID method is to compare the change of CO_2 emissions between pilot and non-pilot provinces before and after pilots implemented. If there is some selection in choosing pilot provinces (see Figure 5.1, pilots emitted less CO_2 and experienced a flatter increase than non-pilots), DID produces biased estimates. One indicator of the existence of selection bias is the violation of parallel pretreatment trend. To relax the often-violated parallel pretreatment trend assumption required by DID, I employed the GSC method to predict the counterfactual CO_2 emissions for pilot provinces.

4.1 Difference-in-Differences

The Kaya identity states that the total CO_2 emission level can be expressed as the product of four factors: carbon intensity, energy intensity, GDP per capita and human population.

$$CO_2 = \frac{CO_2}{Energy} * \frac{Energy}{GDP} * \frac{GDP}{POP} * POP \tag{4.1}$$

Since carbon intensity and energy intensity can be the mechanisms that ETS affects emissions and the initial levels of carbon intensity and energy intensity are absorbed in province fixed effects, I only control for real GDP and population in the model. The DID model is set as follows:

$$Y_{it} = \beta_0 + \beta_1 ETS_{it} + \beta_2 POP_{it} + \beta_3 RGDP_{it} + \lambda_i + \delta_t + \epsilon_{it} \tag{4.2}$$

Where Y_{it} is the log of CO_2 emissions in province i in year t, ETS_{it} is the indicator for ETS pilots after ETS took into effects. POP_{it} and $RGDP_{it}$ are the population and real GDP in logs in province i in year t, respectively. λ_i is province fixed effect, δ_t is year fixed effect. The key coefficient of interest is β_1. Pilots reduce $100\beta_1$% more emissions than non-pilots, which means that ETS reduces $100\beta_1$% emissions if pilots and non-pilots experience parallel trends before and after implementation without ETS.

4.2 Generalized Synthetic Control

The GSC model is set as follows:

$$Y_{it} = \beta_0 + \beta_1 ETS_{it} + \beta_2 POP_{it} + \beta_3 RGDP_{it} + \lambda_i + \delta_t + \sum_m \alpha_{im} f_{tm} + \epsilon_{it} \tag{4.3}$$

The difference of the GSC model from the DID model is the interaction terms between the time-varying coefficients f_{tm} and the province-specific intercepts α_{im}, where m is the number of interaction terms determined by the algorithm. The interaction terms model the unobserved time-varying heterogeneities across provinces.

The GSC model looks the same as the interactive fixed effects (IFE) model proposed by Bai (2009), as incorporating unit-specific intercepts interacted with time-varying coefficients. However, the procedures to estimate GSC and IFE models are different. The steps to obtain IFE estimators are iteratively conducting a factor analysis of the residuals from a linear model and estimating the linear model taking the most influential factors into account while the number of factors is fixed.

The steps to obtain GSC estimators are (1) estimate the IFE model except for the province-specific intercepts α_{im} using only the control group data. Note β_1 cannot be estimated because it is 0 for all control provinces; (2) estimate α_{im} for each treated province by minimizing the mean squared error of the predicted treated outcome in pretreatment periods. α_{im} measures how much each treated province takes up the unobserved continuous time trend; (3) calculate treated counterfactuals based on the estimates of coefficients. The treatment effect is the difference between the real value and the counterfactual. The average treatment effect β_1 is the average of treatment effects across province and period (Xu, 2017).

The GSC method combines the ideas of synthetic control and IFE model. Comparing to synthetic control, GSC can be used in the case of multiple treated units and various treatment periods and produce standard errors for the treatment effect. While IFE imposes a constant treatment effect across unit and period, GSC allows the treatment effect to vary across unit and period. Therefore, GSC corrects the bias under the IFE model when the treatment effect is heterogeneous across units.

Chapter 5

Data

This research employs two key datasets: 1. China Energy Statistical Yearbook, 2. China Statistical Yearbook.

The energy consumption data is drawn from the China Energy Statistical Yearbook 1996-2018. It includes 30 types of energy consumption within China's 30 provincial-level administrative divisions (excluding Tibet, Hong Kong, Macao and Taiwan).[1] Given different energy consumption levels, I selected 13 types of energy to convert the energy consumption to CO_2 emissions.

The carbon emission calculation formula is as shown below:

$$Y_{it} = \sum_j (E_{ijt} * A_j * F_j * O_j) \tag{5.1}$$

Where Y_{it} is the total carbon emissions in province i in year t. E_{ijt} is the consumption of energy j in province i in year t. A_j is the average low calorific value of energy j, drawn from General Administration of Quality Supervision, Inspection and Quarantine, Standardization Administration (2008). F_j is the CO_2 emission factor of energy j and O_j is the carbon oxidation rate of energy j. Both are drawn from Department of Climate Change, National Development and Reform Commission (2011).

[1] Coal total including row coal, cleaned coal, other washed coal, briquettes and gangue, coke, coke oven gas, blast furnace gas, converter gas, other gas, other coking products, petroleum products total including crude oil, gasoline, kerosene, diesel oil, fuel oil, naphtha, lubricants, paraffin waxes, white spirit, bitumen asphalt, petroleum coke, LPG, refinery gas and other petroleum products, natural gas, LNG, heat, electricity and other energy.

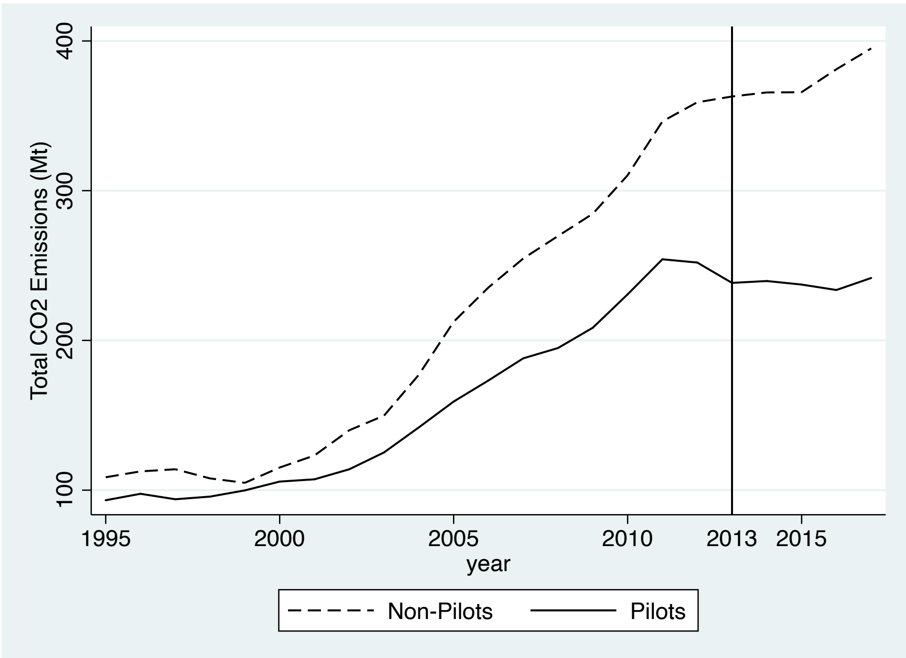
Table 5.1 shows the energy emission coefficients for different types of energy. As for the emission factor, coal is approximately twice as natural gas.

TABLE 5.1: Energy Emission Coefficient

Energy	Average Low Calorific Value (MJ/kg or MJ/cu.m)	Emission Factor (kg CO2/GJ)	Carbon Oxidation Rate	Emission Coefficient (kg/kg or kg/cu.m)
Raw Coal	20.908	96.690	0.91	1.8384
Cleaned Coal	26.344	93.170	0.91	2.2320
Other Washed Coal	8.363	93.170	0.91	0.7086
Coke	28.435	108.167	0.93	2.8604
Coke Oven Gas	17.354	49.793	0.93	0.8036
Crude Oil	41.816	73.700	0.98	3.0202
Gasoline	43.070	69.300	0.98	2.9251
Kerosene	43.070	71.867	0.98	3.0334
Diesel Oil	42.652	74.067	0.98	3.0959
Fuel Oil	41.816	77.367	0.98	3.1705
LPG	50.179	63.067	0.98	3.1013
Refinery Gas	46.055	66.733	0.98	3.0119
Natural Gas	38.931	56.100	0.99	2.1622

Source: General Administration of Quality Supervision, Inspection and Quarantine, Standardization Administration (2008), Department of Climate Change, National Development and Reform Commission (2011).
Emission Coefficient=Average Low Calorific * Emission Factor * Carbon Oxidation/1000

FIGURE 5.1: CO_2 Emission by Pilot



Source: China Energy Statistical Yearbook 1996-2018

Figure 5.1 shows the mean of total emissions in pilot and non-pilot provinces. Since the first ETS was launched in 2013 and the policy was published in 2011, the graph indicates the possibility of expectation effects. The different level of energy consumption between pilot and non-pilot provinces in the pre-pilot time period indicates that there may be some selection bias.

The provincial population, gross output and industrial output data are drawn from China Statistical Yearbook.

5.1 Summary Statistics

Figures 5.2 and 5.3 indicate that the share of electricity, manufacturing, and heating sectors, which I conduct sectoral analysis for, account for about 80% of total CO_2 emissions in both pilot and non-pilot provinces. It is the same case for energy consumption. For both energy consumption and CO_2 emissions, the share of electricity, manufacturing, and heating sectors in pilot provinces is smaller than that in non-pilot provinces. This is inline with the fact that pilot provinces are in more developed regions.

Tables 5.2 and 5.3 present summary statistics. Overall, pilot provinces emit less CO_2 but consume more energy than non-pilot provinces. This is inline with the fact that most pilot areas were selected as low-carbon development regions in 2010. Pilots areas are more developed than non-pilot areas in the sense of real GDP and tertiary industry product ratio [2]. Pilot areas also have less people than non-pilot areas. In looking at Table 5.3, variations of population and real GDP are mainly within variation, which may lead to the high standard error and non-stable estimator of these variables' coefficients.

[2] Per capita emissions in pilots (54.41 kg/person) is less than those in non-pilots (58.48 kg/person). Emissions intensity (emissions to GDP ratio) in pilots (6.09 kg/yuan) is less than those in non-pilots (12.92 kg/yuan).

FIGURE 5.2: Share of CO_2 by Sector

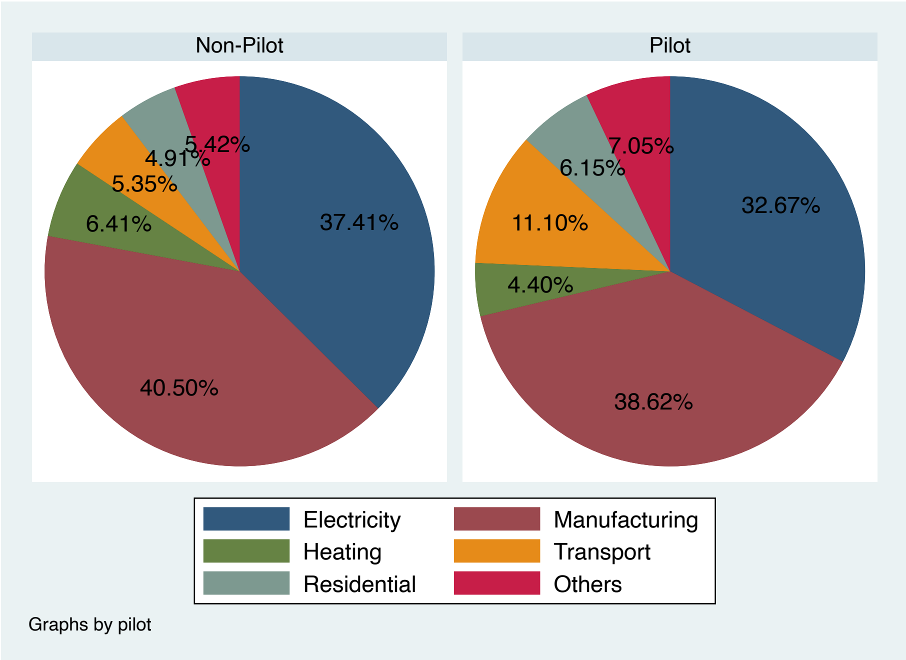


FIGURE 5.3: Share of Energy Consumption by Sector

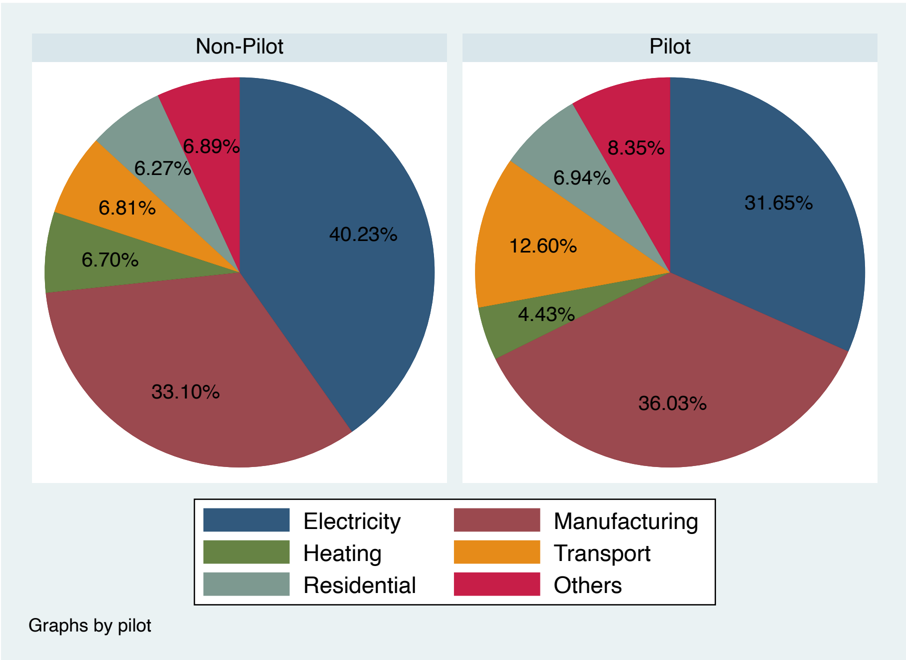


TABLE 5.2: Summary Statistics

	(1) Total	(2) Pilot	(3) Non-Pilot
Total CO_2 Emissions (Megaton)	220.73 (183.09)	171.63 (114.27)	235.63 (197.01)
Electricity CO_2 Emissions (Megaton)	72.40 (70.55)	52.21 (48.85)	78.53 (74.89)
Heating CO_2 Emissions (Megaton)	11.96 (15.33)	7.04 (4.97)	13.46 (17.01)
Manufacturing CO_2 Emissions (Megaton)	79.58 (66.63)	61.71 (39.15)	85.00 (72.10)
Total Energy (Megaton tce)	88.62 (71.47)	70.24 (47.42)	94.20 (76.47)
Electricity Industry Energy (Megaton tce)	28.76 (28.00)	20.95 (19.78)	31.14 (29.67)
Heating Industry Energy (Megaton tce)	4.66 (6.72)	2.93 (2.19)	5.19 (7.50)
Manufacturing Industry Energy (Megaton tce)	25.21 (17.66)	23.85 (15.81)	25.62 (18.18)
Residential Consumption Energy (Megaton tce)	4.80 (3.51)	4.60 (3.48)	4.86 (3.52)
Coal_based Energy (Megaton tce)	68.60 (60.53)	42.07 (28.21)	76.66 (65.25)
Oil_based Energy (Megaton tce)	16.58 (16.04)	24.21 (20.58)	14.26 (13.58)
Natural Gas (Megaton tce)	3.44 (4.38)	3.96 (4.40)	3.28 (4.36)
Real GDP in 2017 (100 million Yuan)	23169.09 (18120.47)	28741.10 (18464.10)	21494.33 (17693.26)
Primary Industry Product Ratio	13.89 (7.62)	7.63 (6.18)	15.78 (6.98)
Secondary Industry Product Ratio	45.87 (7.74)	44.89 (8.41)	46.17 (7.50)
Tertiary Industry Product Ratio	40.24 (8.32)	47.48 (11.60)	38.05 (5.38)
Population (Thousand Persons)	4334.61 (2635.77)	3779.92 (2748.40)	4501.33 (2580.40)

Primary industry includes mining, agriculture, or forestry, that is concerned with obtaining or providing natural raw materials for conversion into commodities and products for the consumer. Secondary industry, or say manufacturing industry, converts the raw materials provided by primary industry into commodities and products for the consumer. Tertiary industry, or say service industry, consists of the production of services, such as access, experience, and affective labor. Standard deviations in parentheses. tce is standard coal equivalent.

TABLE 5.3: Panel Summary Statistics

Variable	Panel	Mean	Sd	Min	Max	Observations
Total CO_2 Emissions	Overall	220.73	183.09	4.40	957.91	N=683
(Megaton)	Between		137.85	24.50	575.80	n=30
	Within		123.10	-154.84	774.56	T=22.77
Total Energy	Overall	240.29	205.47	-545.89	1074.70	N=646
(Megaton tce)	Between		164.77	28.32	734.86	n=30
	Within		124.18	-467.04	686.18	T=21.53
Coal_based Energy	Overall	68.60	60.53	.98	306.74	N=683
(Megaton tce)	Between		48.01	3.79	183.56	n=30
	Within		37.80	-51.18	207.41	T=22.77
Oil_based Energy	Overall	17.24	16.22	0	88.58	N=646
(Megaton tce)	Between		13.09	2.03	61.72	n=30
	Within		9.51	-15.92	50.98	T=21.53
Natural Gas	Overall	157.34	153.58	-581.26	807.50	N=646
(Megaton tce)	Between		125.77	18.42	593.22	n=30
	Within		87.51	-513.62	465.40	T=21.53
Real GDP in 2017	Overall	23169.09	18120.46	1479.29	89705.23	N=688
(100 Million Yuan)	Between		17677.16	2157.75	69043.65	n=30
	Within		5014.21	7020.37	43830.67	T=22.93
Primary Industry	Overall	13.89	7.62	.361	37.91	N=659
Product Ratio	Between		6.30	1.15	30.97	n=30
	Within		4.43	4.41	29.84	T=21.97
Secondary Industry	Overall	45.87	7.74	19.01	61.48	N=659
Product Ratio	Between		6.23	24.19	53.08	n=30
	Within		4.71	22.77	58.70	T=21.97
Tertiary Industry	Overall	40.24	8.32	24.64	80.56	N=659
Product Ratio	Between		6.76	31.87	68.52	n=30
	Within		4.99	24.28	59.09	T=21.97
Population	Overall	4334.61	2635.77	481	11430	N=688
(Thousand Persons)	Between		2650.38	544.26	9431.48	n=30
	Within		364.83	1905.40	7282.31	T=22.93

Chapter 6

Results

6.1 Aggregate and Sectoral Analysis

Aggregate analysis gives a sense of total CO_2 emissions reduction caused by ETS. Sectoral analysis is necessary for three reasons: (1) As indicated in Table 3.2 and 3.3, Chinese provincial ETS doesn't cover coal washing and coking, agriculture, forestry, animal husbandry and fishing, and residential consumption. (2) As indicated in Table 3.1, ETS is more strict in the manufacturing sector than other sectors. Sectoral analysis allows to capture the heterogeneous effects of ETS across sectors. (3) General Office of the State Council (2013) requires industrial heating enterprises' facilities in the Beijing-Tianjin-Hebei Region and surrounding areas[1], the Yangtze River Delta Region[2], the Pearl River Delta Region [3], and Chongqing to switch from coal to natural gas since 2013. It also requires 2 key industries such as steel and cement to eliminate outdated production capacity production and implement cleaner production technology. This policy covers all of ETS pilot provinces except Hubei, which may contaminate the analysis of ETS. Therefore, it is necessary to organize the economy as a set of multiple sectors and mostly importantly, separate the electricity sector that is not affected by the Air Pollution Control Action Plan.

[1] Beijing, Tianjin, Hebei Province, Shanxi Province, Inner Mongolia Autonomous Region, and Shandong Province

[2] Shanghai, Jiangsu Province, and Zhejiang Province

[3] Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, and Zhongshan in Guangdong Province

6.1.1 Aggregate Analysis

Table 6.1 presents DID and GSC regression results for 30 provinces over the time period 1995-2017. The DID regression results show that ETS leads to a 32.3% CO_2 emissions reduction. The GSC regression results show that ETS leads to a 9.7% CO_2 emissions reduction, which is not statistically significant at the 10% significance level.

Figures 6.1 and 6.2 explain the reason of the different effects estimated from DID and GSC. DID requires the parallel trend assumption in the pretreatment period to compare the change of CO_2 emissions between ETS and non-ETS provinces. Figure 6.1 indicates that non-ETS provinces experienced a greater CO_2 emissions increase in the pretreatment period than ETS provinces. Therefore, the DID estimate is likely to be biased downward. After taking into account the continuous time trend each ETS province takes up, Figure 6.2 presents that the pretreatment trend of the counterfactual emissions is similar to that of ETS provinces' emissions. Therefore, the average treatment effect of GSC is more likely to be unbiased comparing to that of DID. Table 6.1 shows that while using GSC to alleviate the selection bias problem of DID, ETS does not reduce the aggregate emissions.

The takeaway is that emissions reduction is lower when pre-treatment trends are properly controlled for. My DID result (32.3% CO_2 emissions reduction) is greater than that of Hu et al. (2020) (15.5%). It can be caused by the fact that Hu et al. (2020) controlled for more variables: foreign direct investment, technological innovation, etc. This is inline with the result that when choosing a better control group (in this case: controlling for more characteristics), emissions reduction is lower. I cannot compare my GSC result with that of Zhang et al. (2019) because Zhang et al. (2019) only provide graphs to compare emission reductions across pilots and sectors and does not provide any estimated coefficients.

The reasons that ETS does not reduce the aggregate emissions may be: (1) As indicated in Table 3.2, ETS covers only 40-60% of the aggregate emissions in pilot areas. Even though ETS covers manufacturing, electricity, heating and other sectors which counts for more than 80% of the aggregate emissions, only firms that emit above a threshold are covered by ETS. (2) As shown in Table 3.1, the firm-level cap is loose in ETS-covered sectors except manufacturing.

As for GDP and Population, Column (4) indicates that a 100% increase in real GDP leads to a 66.2% increase in CO_2 emissions and a 100% increase in population leads to a 167.1% increase in CO_2 emissions.

TABLE 6.1: Aggregate Analysis

	DID		GSC	
	(1)	(2)	(3)	(4)
ETS	-0.309***	-0.323***	0.041	-0.097
	(0.099)	(0.080)	(0.059)	(0.134)
GDP		0.456		0.662*
		(0.379)		(0.284)
Population		0.027		1.671***
		(0.490)		(0.569)
Observations	683	683	683	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FIGURE 6.1: DID Aggregate Analysis

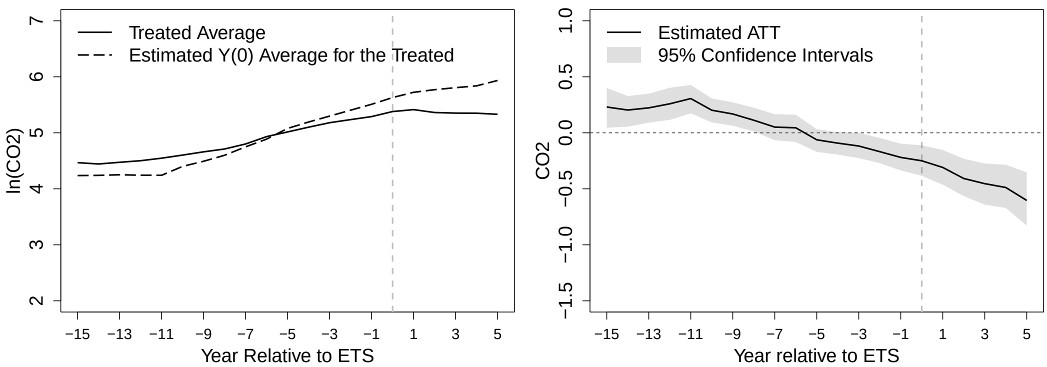
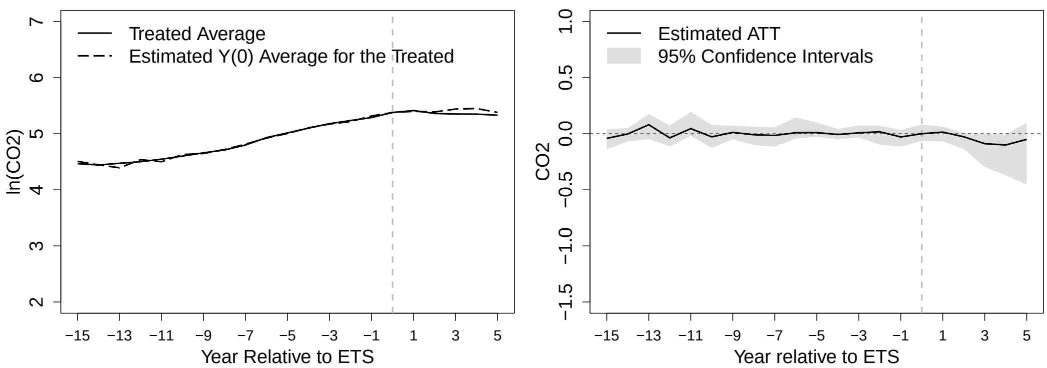


FIGURE 6.2: GSC Aggregate Analysis



6.1.2 Electricity Sector

According to Figure 5.2, the electricity sector accounts for about 35% of the aggregate emissions. As shown in Table 6.2, the results from the electricity sector tell a similar story as the aggregate analysis. The DID regression results show that ETS leads to a 26.9% CO_2 emissions reduction. The GSC regression results show that ETS leads to a 7.1% CO_2 emissions reduction, which is not statistically significant at the 10% significance level. Again, Figures 6.3 and 6.4 explain the reason of the different effects estimated from DID and GSC: whether the pretreatment parallel trend assumption is satisfied. While using GSC to alleviate the selection bias problem of DID, ETS does not reduce CO_2 emissions in the electricity sector.

The analysis of the electricity sector is not affected by the Air Pollution Control Action Plan (APCA) conducted in the heating sector. The above results mean that ETS does not reduce much of CO_2 emissions. The possible reason is the loose firm-level cap and benchmark in the electricity sector, even with double counting. This should have implications for the Chinese national carbon trading scheme conducting solely in the electricity sector starting from 2020.

TABLE 6.2: Electricity Sector Analysis

	DID		GSC	
	(1)	(2)	(3)	(4)
ETS	-0.271**	-0.269**	-0.069	-0.071
	(0.132)	(0.123)	(0.099)	(0.157)
GDP		0.720		1.037
		(0.478)		(0.332)
Population		-0.103		2.015
		(0.696)		(0.784)
Observations	683	683	683	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FIGURE 6.3: DID Electricity Sector Analysis

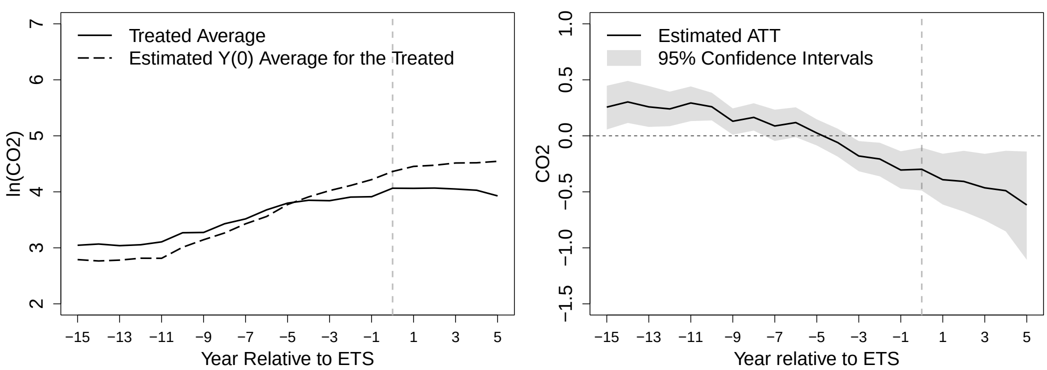
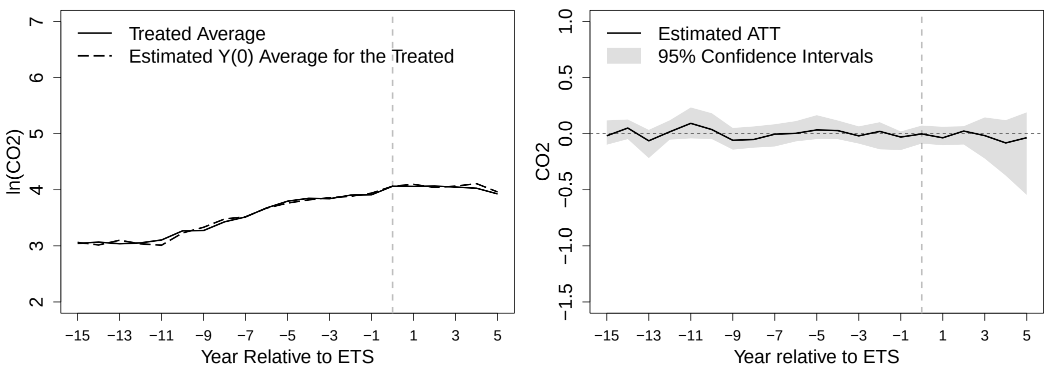


FIGURE 6.4: GSC Electricity Sector Analysis



6.1.3 Heating Sector

According to Figure 5.2 the heating sector accounts for about 5% of the aggregate emissions. As shown in Table 6.3, the results from the heating sector present a different story from the aggregate and the electricity sector analysis. The DID regression results show that ETS leads to a 31.1% CO_2 emissions reduction. The GSC regression results show that ETS leads to a 30.1% CO_2 emissions reduction, which is not statistically significant at the 10% significance level.

The heating sector of most pilot provinces experienced both ETS and APCA. The timings of ETS and APCA overlap for all pilot provinces except Fujian. Thus, the coefficient of ETS is approximately the coefficient of ETS and APCA. The estimates of the coefficient are large but reasonable because natural gas emits half amount of CO_2 as coal when generating the same amount of caloric according to the emission factors presented in Table 5.1.

Because the firm-level cap for both the heating and electricity sectors are loose, a simple comparison of the results from heating and electricity sectors is able to distinguish the CO_2 emissions reduction effects of ETS and APCA. The story here is that besides ETS, APCA also reduce emissions.

Northern provinces provide central heating for business and houses, thus most heating firms locate in northern provinces.The estimated coefficient of the interaction term between northern provinces and ETS indicates that ETS and APCA reduce 39.6% more CO_2 emissions in northern provinces than in southern provinces.

TABLE 6.3: Heating Sector Analysis

	DID			GSC	
	(1)	(2)	(3)	(4)	(5)
ETS	-0.300	-0.311	-0.076	-0.269	-0.301
	(0.297)	(0.326)	(0.623)	(0.221)	(0.280)
GDP		0.129	0.150		0.020
		(0.966)	(0.963)		(0.926)
Population		0.040	0.078		2.192
		(1.125)	(1.119)		(1.658)
Northern*ETS			-0.396		
			(0.652)		
Observations	662	662	662	662	662

Northern*ETS is omitted under GSC. Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. Northern is a dummy for northern provinces. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FIGURE 6.5: DID Heating Sector Analysis

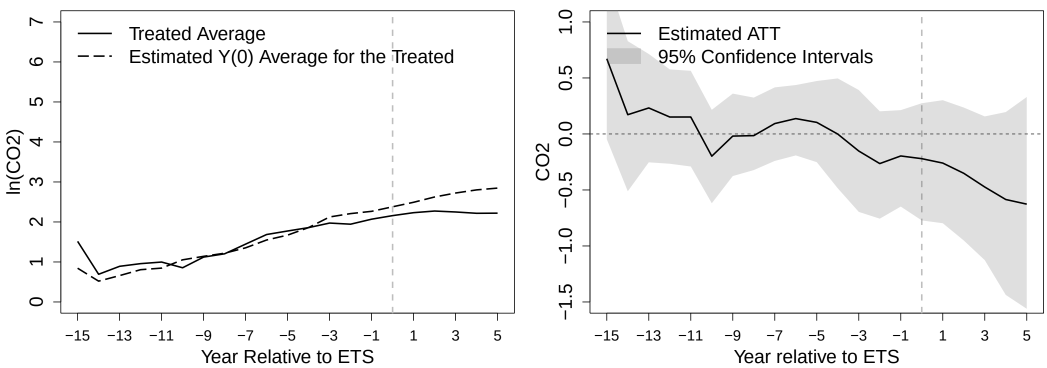
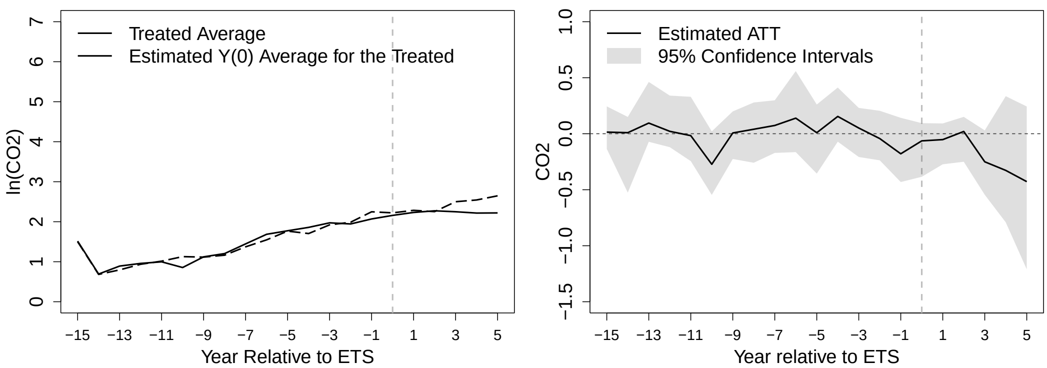


FIGURE 6.6: GSC Heating Sector Analysis



6.1.4 Manufacturing Sector

According to Figure 5.2, the manufacturing sector accounts for about 40% of the aggregate emissions. The manufacturing sector is different from the electricity sector because ETS only covers a portion of industries in the manufacturing sector. The manufacturing sector is different from the heating sector because APCA only covers part of industries in the manufacturing sector.

The DID regression results show that ETS leads to a 51.1% CO_2 emissions reduction. The GSC regression results show that ETS leads to a 17.3% CO_2 emissions reduction, which is statistically significant at the 10% significance level. This estimated coefficient combines the facts that (1) manufacturing experienced both ETS and APCA; (2) the firm-level cap is strict in the manufacturing sector; (3) not all industries in the manufacturing sector are covered by ETS.

TABLE 6.4: Manufacturing Sector Analysis

	ETS		GSC	
	(1)	(2)	(3)	(4)
ETS	-0.578**	-0.511***	-0.150*	-0.173*
	(0.258)	(0.180)	(0.093)	(0.181)
GDP		0.092		0.599*
		(0.537)		(0.336)
Population		-0.594		0.897*
		(0.685)		(0.888)
Observations	683	683	683	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FIGURE 6.7: DID Manufacturing Sector Analysis

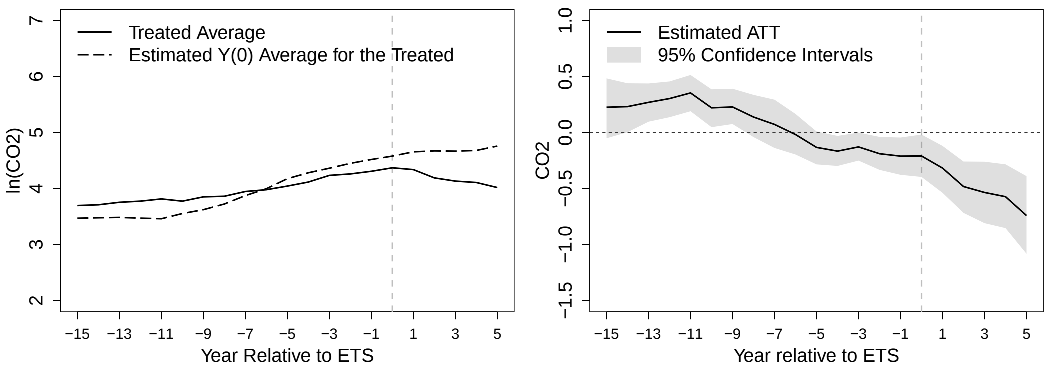
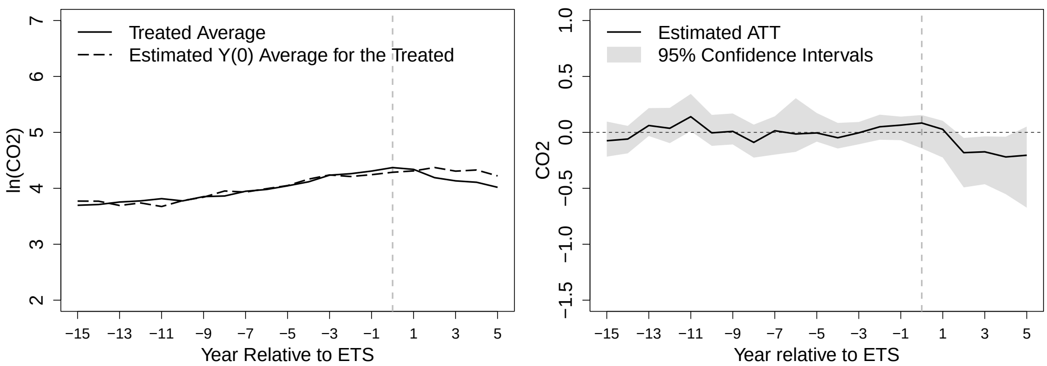


FIGURE 6.8: GSC Manufacturing Sector Analysis



6.2 Expectation Effect

At the end of 2011, the NDRC issued the Notice on the Pilot Work on Carbon Emission Trading. It took 2-3 years for the pilots to launch ETS. One may be concerned about whether there is any expectation effect, that is, whether the effect of ETS happened before the date of ETS took into effect. Indeed, Figure 5.1 indicates that the flatter growth of total CO_2 emissions for both pilot and non-pilot provinces started from 2011. To address this concern, I conduct two approaches to test for the expectation effect, following Cai et al. (2016).

First, I include an additional control indicating years between the issue date of the NDRC notice (2011) and the implementation year (2013, 2014 or 2016) for each pilot in the regression. The results in Table 6.5 present no significant expectation effects for the aggregate, electricity, heating, and manufacturing sectors analyses and the corresponding estimated coefficients of ETS barely change.

TABLE 6.5: Expectation Effect DID Analysis

	(1) Aggregate	(2) Electrcity	(3) Heating	(4) Manufacturing
ETS	-0.356***	-0.290*	-0.109	-0.486**
	(0.100)	(0.151)	(0.350)	(0.186)
Expectation	-0.126	-0.077	0.135	-0.214
	(0.115)	(0.174)	(0.279)	(0.166)
GDP	0.418	0.697	0.181	-0.029
	(0.384)	(0.481)	(0.994)	(0.576)
Population	0.111	-0.052	-0.171	-0.356
	(0.464)	(0.683)	(1.254)	(0.685)
Constant	-0.474	-3.146	0.304	6.674
	(5.871)	(8.192)	(9.607)	(9.496)
Observations	683	683	662	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. Expectation is 1 for pilot provinces between 2011 and the year of ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Second, I use 2011 as the time of treatment instead of the real effective date for each pilot. If there is no expectation effect, the estimation using 2011 as the time of treatment should be less statistically significant or greater in magnitude. Indeed, as shown in Table 6.6 the estimates of ETS for the aggregate, electricity, heating and manufacturing sector analyses (-0.259***, -0.200, -0.006, -0.415**) are less statistically significant and greater in magnitude than those (-0.323***, -0.269**, -0.311, -0.511***) using the real effective date as the time of treatment, respectively.

TABLE 6.6: Expectation Effect DID Analysis

	(1) Aggregate	(2) Electrcity	(3) Heating	(4) Manufacturing
ETS	-0.259**	-0.200	-0.006	-0.415**
	(0.109)	(0.157)	(0.315)	(0.199)
GDP	0.399	0.679	0.160	-0.001
	(0.389)	(0.487)	(0.989)	(0.564)
Population	0.058	-0.101	-0.228	-0.541
	(0.464)	(0.678)	(1.254)	(0.643)
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	683	683	662	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces 2011 onwards. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.3 Mechanism Analysis

6.3.1 Energy Structure

Types of energy can be classified as coal-based energy, oil-based energy and natural gas. Firms can convert from dirty energy to clean energy to reduce emissions. According to the emission factors in Table 5.1, to produce the same amount of caloric, coal-based energy emits most CO_2 and natural gas emits least CO_2.

Based on the conversion factors from physical units to coal equivalent of Chinese Energy Statistical Yearbook, I convert coal total, petroleum products total, and natural gas to the equivalent standard coal and calculate the ratio of each type of energy to the total energy.

Table 6.7 presents the results of energy structure analysis at the aggregate level. ETS reduces coal-based energy consumption by 8.787 percentage points and increases natural gas and oil-based energy consumption by 5.090 and 3.697 percentage points, respectively. All of the three estimates are statistically significant at at least the 5% significance level.

Table 6.8 presents the results of energy structure analysis in the electricity sector. ETS reduces coal-based and oil-based energy consumption by 9.581 and 0.854 percentage points, respectively, and increases natural gas consumption by 10.435 percentage points, which is statistically significant at the 10% significance level.

Table 6.9 presents the results of energy structure analysis in the heating sector. The whole sample results show that ETS reduces coal-based energy consumption by 13.379 percentage points (statistically at the 5% significance level) and increases natural gas and oil-based energy consumption by 4.176 and 9.203 percentage points, respectively.

The magnitude of the coefficient of coal-based energy in the heating sector is greater than that in the electricity sector along with the fact that energy consumption in the heating sector (44.52% and 35.90%) is about 7 times of that in the heating sector (7.42% and 5.02%) as shown in Figure 5.3 indicates the strictness of APCA (All coal-based heating installations have to switch to natural gas or stop producing by 2017).

Table 6.10 presents the results of energy structure analysis in the manufacturing sector. ETS barely changes coal-based, oil-based energy, or natural gas consumption. That is to say, switching from dirty energy to clean energy is not the mechanism of CO_2 emissions reduction in the manufacturing sector.

Overall, ETS reduces emissions in the electricity and heating sectors through energy structure.

TABLE 6.7: Energy Structure Aggregate Analysis

	(1) Coal	(2) Oil	(3) Natural Gas
ETS	-8.787**	5.090*	3.697*
	(3.485)	(2.569)	(1.808)
GDP	-1.811	-3.288	5.099
	(9.142)	(6.778)	(4.359)
Population	-12.119	-3.703	15.822**
	(15.147)	(12.708)	(5.916)
Constant	195.767	78.660	-174.427**
	(172.452)	(109.291)	(75.099)
Observations	683	683	683

Dependent variable is the ratio of each type of energy. ETS is 1 for pilot provinces after 2011 and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.8: Electricity Sector Energy Structure Analysis

	(1) Coal	(2) Oil	(3) Natural Gas
ETS	-9.581	-0.854	10.435
	(7.000)	(1.856)	(6.441)
GDP	-14.969	3.520	11.449
	(10.753)	(2.566)	(11.353)
Population	-6.823	-17.496**	24.319
	(15.480)	(8.157)	(14.944)
Constant	292.715	111.827**	-304.542
	(206.857)	(51.030)	(206.319)
Observations	683	683	683

Dependent variable is the ratio of each type of energy to the total energy. ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.9: Heating Sector Energy Structure Analysis

	(1) Coal	(2) Oil	(3) Natural Gas
ETS	-13.379**	4.176	9.203
	(6.356)	(3.243)	(5.797)
GDP	-3.290	-9.085	12.375
	(8.095)	(9.217)	(7.328)
Population	9.669	-21.032*	11.363
	(11.825)	(11.354)	(9.410)
Constant	43.366	266.055**	-209.421*
	(101.455)	(122.072)	(115.695)
Observations	663	663	663

Dependent variable is the ratio of each type of energy to the total energy. ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.10: Manufacturing Sector Energy Structure Analysis

	(1) Coal	(2) Oil	(3) Natural Gas
ETS	0.213	-0.316	0.103
	(4.225)	(3.592)	(1.654)
GDP	8.424	-15.350*	6.925
	(8.293)	(8.150)	(5.059)
Population	-43.604***	24.282*	19.323***
	(11.441)	(12.726)	(5.715)
Constant	348.301***	-30.329	-217.972***
	(111.640)	(115.322)	(39.074)
Observations	683	683	683

Dependent variable is the ratio of each type of energy to the total energy. ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.3.2 Energy Consumption Analysis

Table 6.11 indicates that ETS reduces 0.243/20.95=1.16% energy consumption in the electricity sector (statistically significant at the 10% significance level), 0.277/23.85=1.16% energy consumption in the manufacturing sector (statistically significant at the 5% significance level), 0.177/2.93=6.04% energy consumption in the heating sector (not statistically significant at the 10% significance level). Aggregately, ETS reduces 0.255/70.24=0.36% energy consumption (statistically significant at the 1% significance level).

TABLE 6.11: Energy Consumption Analysis

	(1) Aggregate	(2) Electricity	(3) Heating	(4) Manufacturing
ETS	-0.255***	-0.243**	-0.177	-0.276**
	(0.070)	(0.112)	(0.270)	(0.123)
GDP	0.509	0.863*	0.078	0.110
	(0.348)	(0.437)	(1.075)	(0.377)
Population	-0.001	-0.086	0.373	0.282
	(0.408)	(0.662)	(1.242)	(0.449)
Constant	-1.354	-5.385	-4.024	-0.881
	(5.195)	(7.602)	(9.088)	(6.349)
Observations	683	683	661	683

Dependent variable is ln(energy consumption (megaton tce)). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Combining with the results from the energy structure analysis, we conclude that ETS reduces CO_2 emissions in the electricity sector via adjusting energy structure and energy consumption, the heating sector via adjusting energy structure, and the manufacturing sector via decreasing energy consumption.

6.3.3 Industry Structure

ETS can reduce emissions by affecting industry structure. Table 6.12 presents that it is not the case for Chinese provincial ETS. ETS increases tertiary industry product ratio by 0.337 percentage point, reduces primary and secondary product ratio by 0.131 and 0.206 percentage point, respectively. None of the estimates is significant at the 10% significant level.

TABLE 6.12: Industry Structure Analysis

	(1) Primary	(2) Secondary	(3) Tertiary
ETS	-0.131	-0.206	0.337
	(0.627)	(1.316)	(1.150)
GDP	-10.500**	16.019*	-5.519
	(4.012)	(8.648)	(5.817)
Population	16.920***	-30.284***	13.363
	(2.493)	(9.244)	(7.888)
Constant	-13.863	134.938	-21.076
	(45.064)	(121.143)	(86.050)
Observations	659	659	659

Dependent variable is the percentage point of each industry's product to the gross regional product. ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.4 Heterogeneous Effect

Wang et al. (2017) proposed the National Economic Research Institute index to measure provincial economic liberalization level. The NERI index consists of five subindexes: the ratio of economic resources distributed by market, development of non-state economy, development of product market, development of factor market, and market intermediary organization development and legal system environment. I use the average index from 2013 to 2016[4] to distinguish higher and lower economic liberalization provinces. All pilot provinces are in the higher economic liberalization group, so I conduct analysis using solely higher economic liberalization provinces.

The DID results are in Tables 6.13, 6.14, 6.15, and 6.16. The comparison between columns (2) and (4) in each table shows that the emission reduction effect of ETS is smaller when choosing a more appropriate control group - higher economic liberalization provinces. This is consistent with the GSC results. Take Table 6.13 as an example, the result in the higher economic liberalization group shows that ETS leads to a 8.8% CO_2 emissions reduction, which is smaller than the analysis in the total provinces and comparable with the GSC result (9.7%) in Table 6.1.

[4]2017 index is not available.

TABLE 6.13: Heterogeneous Effect Aggregate DID Analysis

	Total		Higher Liberalization	
	(1)	(2)	(3)	(4)
ETS	-0.309***	-0.323***	-0.185**	-0.088
	(0.099)	(0.080)	(0.083)	(0.051)
GDP		0.456		-0.467
		(0.379)		(0.458)
Population		0.027		-0.455
		(0.490)		(0.338)
Constant	4.393***	-0.160	4.742***	13.279**
	(0.050)	(6.025)	(0.052)	(5.285)
Observations	683	683	315	315

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.14: Electricity Sector Heterogeneous Effect DID Analysis

	Total		Higher Liberalization	
	(1)	(2)	(3)	(4)
ETS	-0.271**	-0.269**	-0.150	-0.097
	(0.132)	(0.123)	(0.158)	(0.075)
GDP		0.720		-0.546
		(0.478)		(0.677)
Population		-0.103		-0.093
		(0.696)		(0.735)
Constant	3.052***	-2.954	3.367***	9.671
	(0.060)	(8.267)	(0.095)	(8.151)
Observations	683	683	343	343

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.15: Heating Sector Heterogeneous Effect DID Analysis

	Total		Higher Liberalization	
	(1)	(2)	(3)	(4)
ETS	-0.300	-0.311	-0.243	-0.100
	(0.297)	(0.326)	(0.279)	(0.322)
GDP		0.129		0.112
		(0.966)		(0.938)
Population		0.040		-0.918
		(1.125)		(1.162)
Constant	0.648***	-0.902	1.193***	7.719
	(0.134)	(8.875)	(0.164)	(8.165)
Observations	662	662	343	343

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6.16: Manufacturing Sector Heterogeneous Effect Analysis

	Total		Higher Liberalization	
	(1)	(2)	(3)	(4)
ETS	-0.578**	-0.511***	-0.441	-0.264*
	(0.258)	(0.180)	(0.259)	(0.130)
GDP		0.092		-1.113
		(0.537)		(0.889)
Population		-0.594		-0.721
		(0.685)		(0.497)
Constant	3.527***	7.440	3.962***	21.240*
	(0.069)	(9.340)	(0.085)	(10.646)
Observations	683	683	343	343

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Chapter 7

Robustness Check

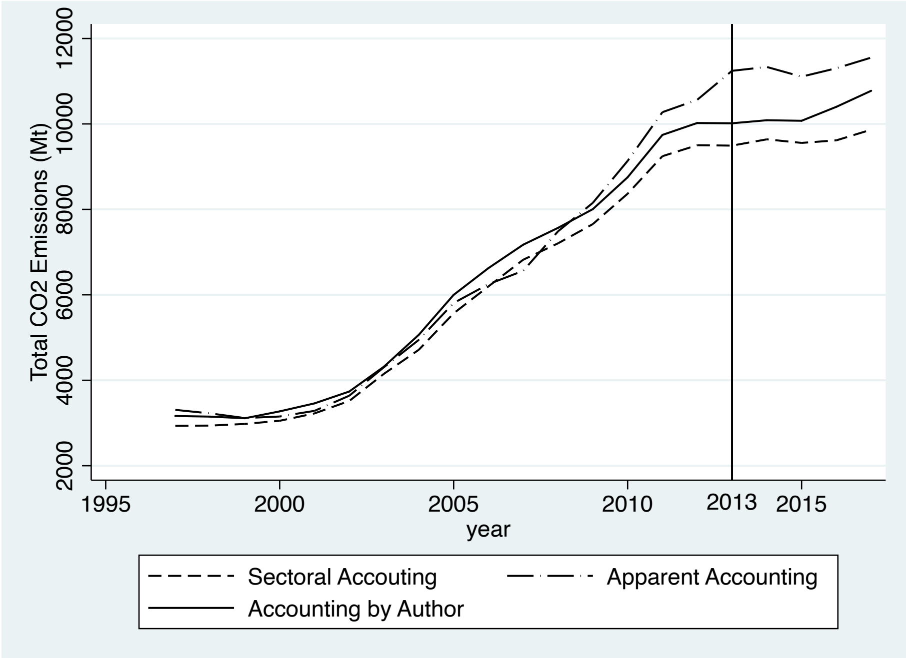
7.1 Analysis with CEADs Data

Figure 7.1 shows the national emissions from different sources. The sectoral and apparent accounting data come from China Emission Accounts and Datasets (CEADs). The national CO_2 emissions calculated by me is between the sectoral accounting and apparent accounting[1] results, which gives credibility to my results. The sectoral and apparent accounting data are also used as a robustness check.

I apply the DID method with the apparent and sectoral accounting emissions data as a robustness check. Because heating and electricity sectors are not separable in the sectoral accounting data, I cannot do a robustness check for sectoral analysis. The estimated coefficient with my data is between those with the apparent and sectoral accounting data for both DID and GSC approaches. The results from any data sources indicate that the emissions reduction effect is lower while using GSC to alleviate the selection bias problem of DID.

[1] According to the Intergovernmental Panel on Climate Change (2006), apparent accounting, also named as reference accounting, is a top-down approach, using a countrys' energy supply data to calculate the CO_2 emissions from combustion of mainly fossil fuels (apparent consumption=production+imports-exports-international bunkers-stock change); sectoral accounting is using a countrys' sectoral energy final consumption data to calculate the CO_2 emissions.

FIGURE 7.1: CO_2 Emission by Source



Source: China Energy Statistical Yearbook 1996-2018 and China Emission Accounts and Datasets (CEADs)

TABLE 7.1: Comparative Analysis with CEADs Data

	Author		Apprent		Sectoral	
	(1)	(2)	(3)	(4)	(5)	(6)
	DID	GSC	DID	GSC	DID	GSC
ETS	-0.280***	-0.195*	-0.381***	-0.094	-0.255***	–0.232**
	(0.074)	(0.147)	(0.109)	(0.087)	(0.069)	(0.116)
GDP	0.424	0.715**	1.549**	0.293	0.391	0.667
	(0.374)	(0.262)	(0.687)	(0.369)	(0.334)	(0.278)
Population	-0.181	1.895**	-0.533	-1.125	-0.358	1.301*
	(0.528)	(0.647)	(0.637)	(1.303)	(0.489)	(0.742)
Observations	625	625	630	630	626	626

Year: 1997-2017. Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. All regressions include year and province fixed effects. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7.2 Placebo Test

To confirm that the significant emissions reduction result from the DID approach is not the placebo effect, I randomly select seven non-pilot provinces and treat them as pilots to rerun the regression. As shown in Table 7.2, ETS does not reduce emissions significantly in any of the sectors or aggregately. The comparison between the estimated coefficients of ETS in Table 7.2 and the DID estimated coefficients of ETS in Tables 6.1, 6.2, 6.3, and 6.4 (-0.323***, -0.269***, -0.311, and -0.511***) respectively shows that the emissions reduction effects of ETS are not placebo effects.

TABLE 7.2: Placebo Test (DID)

	(1) Aggregate	(2) Electricity	(3) Heating	(4) Manufacturing
ETS	0.015	-0.076	0.072	-0.115
	(0.098)	(0.129)	(0.195)	(0.103)
GDP	0.508	0.750	0.173	0.077
	(0.396)	(0.488)	(0.967)	(0.572)
Population	-0.311	-0.425	-0.204	-0.986
	(0.540)	(0.719)	(1.131)	(0.853)
Constant	2.069	-0.652	0.643	10.741
	(6.562)	(8.638)	(8.783)	(10.824)
Observations	683	683	662	683

Dependent variable is ln(carbon dioxide emissions). ETS is 1 for pilot provinces after ETS implementation and 0 for others. GDP and population are in logs. Standard errors in parentheses are clustered at the province level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Chapter 8

Conclusion

This paper employs the DID and GSC methods to test whether Chinese ETS pilots reduce CO_2 emissions. The aggregate DID analysis indicates that ETS reduces 32.3% emissions. While using GSC to alleviate the selection bias problem of DID, ETS reduces 9.7% emissions (not statistically significant at the 10% significance level). The sectoral analysis in electricity, heating, and manufacturing tells a similar story. That is to say, ETS pilots did reduce emissions, but by less than expected.

The expectation effect analysis shows no evidence of an expectation effect. The mechanism analysis indicates that ETS reduces emissions in the electricity sector via adjusting energy structure and decreasing energy consumption, the heating sector via adjusting energy structure, and the manufacturing sector via decreasing energy consumption. The heterogeneous effect analysis indicates that while choosing higher economic liberalization provinces instead of all provinces as the sample, the emission reduction effect of ETS is small. This is consistent with the GSC results because higher economic liberalization provinces construct a more appropriate control group than all provinces.

Further research can be done by (1) conducting industry-level analysis to get closer to emissions covered by ETS given the fact that not all industries in the manufacturing sector are covered by Chinese ETS pilots. (2) digging more into the design of Chinese ETS pilots and testing related economic theory. For example, whether bottom-up or cap setting has better performance in reducing emissions, and whether double-counting helps reduce emissions.

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