The Effectiveness of China's Regional Carbon Market Pilots in Reducing Firm Emissions

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1 Policy Background

As the world's largest greenhouse gas (GHG) emitter, China has gradually embodied climate change initiatives in its development planning. In the 2009 Copenhagen Accord, China pledged to reduce its carbon intensity, measured by carbon emissions per unit of GDP, by 40 to 45 percent from the 2005 level by 2020. On October 29, 2011, the National Development and Reform Commission (NDRC) formally approved seven regional carbon emission trading system (ETS) pilots, covering four municipalities (Beijing, Shanghai, Tianjin, and Chongqing), one special economy zone (Shenzhen), and two provinces (Guangdong and Hubei).[1] These pilots began trading carbon allowances in 2013 and 2014.[2] The pilot regions are granted flexibility in designing their own carbon market rules following some general guidelines from the NDRC. Each pilot has the discretion to determine covered sectors, emission targets, allowance allocation, monitoring, reporting and verification (MRV), and compliance (Zhang, Wang, and Du, 2017), while the NDRC oversees the planning and development of ETS. Table S1 provides a summary of ETS policies across pilots.

The pilot ETS has three distinct features. First, it experienced two important phases: announcement (2011 to 2012) and trading (since 2013). During the announcement phase, there existed considerable uncertainty about the coverage and stringency of ETS pilots. Without a list of regulated entities, carbon market prices, and detailed implementation rules, firms in pilot regions may not have had clear expectations regarding their emission reduction paths. Thus, the announcement effect on emission abatement would likely differ dramatically from the trading effect. Therefore, our empirical analysis differentiates the ETS effects between the announcement effect and the trading effect.

[1] Shenzhen is a sub-provincial city located in Guangdong province but establishes an independent ETS pilot. The firms regulated by the Shenzhen ETS are not covered by the Guangdong ETS.

[2] The first ETS pilot was launched by Shenzhen in June 2013, followed by Shanghai, Beijing, Guangdong, and Tianjin in the same year. The remaining pilots, Hubei and Chongqing, launched ETS in April and June in 2014, respectively. Fujian province opted to launch the eighth carbon market pilot in December 2016, which is beyond our sample period.

Second, the pilot ETS exhibits significant heterogeneity in policy design. The covered sectors vary across pilots, ranging from manufacturing to non-manufacturing industries. The threshold of coverage is determined by annual emissions or energy consumption, resulting in various total emission allowances across pilots.[3] While almost all pilots allocate allowances for free,[4] carbon allowances can only be traded within the same pilot, with the result that carbon price and trading activity vary across pilots. Further, each pilot has established its own MRV (measurement, reporting, and verification) system, although the pilots share similar protocols, in which noncompliances is subject to financial and non-financial penalties.[5] The policy variations across sectors and regions enable us to identify different carbon market outcomes.

Third, China's regional ETS used two main allowance allocation rules: mass-based and rate-based. Under the mass-based (cap-and-trade) system (Goulder and Morgenstern, 2018; Goulder et al., 2019), regulators set a total number of allowances – an emission cap – in advance of each compliance period. Each covered facility receives allowances based on its historical emission level (e.g., Phases I & II in the EU ETS) or the product of a pre-established benchmark emission-output ratio and some fixed reference production quantity (e.g., Phase III in the EU ETS, cap-and-trade in California and Quebec). If a covered facility's emission level exceeds the pre-established number of allowances, it must purchase additional allowances from the carbon market to achieve compliance. In most cases, the allowance allocation is exogenous to a facility's production level during the compliance period.[6]

[3]Guangdong issues the most carbon allowances (388 Metric tons [Mt]), while Shenzhen has the least (30 Mt). The covered shares of emissions in each pilot range from 33 percent for Hubei to 60 percent for Tianjin.

[4]The exception is that that Guangdong and Shenzhen auction a small share of allowances – up to 3 percent.

[5]These include deduction of excessive emissions from the allowance allocation next year, and records of noncompliance in the business credit reporting systems.

[6]There are a few exceptions. If the allowance allocation under the cap-and-trade system is output-based and therefore endogenous, the allowances allocated to a covered firm could be updated based on the production level in the previous compliance period (Goulder et al., 2019). The purpose of such output-based allocation is to mitigate carbon leakage and safeguard the competitiveness of covered facilities by subsidizing additional output with extra allowances (Fowlie, Reguant, and Ryan, 2016; Goulder et al., 2019). In some cap-and-trade systems, the output-based allocation under the cap-and-trade system has been applied to

Some ETS pilots have adopted tradable performance standards, which is a rate-based system (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019). The regulators set an emission intensity ratio – a performance standard or rate – rather than an emission cap for covered firms. The number of allowances depends on output level and a benchmark or historical emission rate. The total number of allowances is not determined until the end of each compliance period when a firm's production level is observed. As an ex-post adjustment, the allowance is thus endogenous within each compliance period.[7] This system can be regarded as an implicit subsidy to firm production since additional output value increases the number of allowances that covered firms receive (Fischer, 2001; Fischer and Newell, 2008). Such flexibility puts less compliance pressure on regulated firms but compromises cost-effectiveness in achieving climate targets (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2019). Table S2 summarizes detailed information about allowance allocation rules across pilots.

2 Data Cleaning

This section documents the data cleaning process. (i) We remove observations with missing or zero values in output value, sales, emissions, and energy consumption of fuels. Around 20.9% of firms are dropped from the sample for this reason. (ii) We drop the regulated firms whose carbon emissions or energy consumption levels during the pre-ETS period are smaller than the coverage thresholds of ETS pilots (as shown in Table S1). This results in removal of 191 ETS firms, around 0.03% of all firms in our sample, from the sample. (iii) Next, we drop observations whose key variables (output value, emission, and emission intensity) have drastic changes across years. In our analysis, any

only a small subset of facilities that are in emissions-intensive and trade-exposed sectors.

[7]Under a rate-based system, covered firms receive carbon allowances through a two-step process. At the beginning of a compliance period, each covered firm receives initial allowances based upon its output value in the previous period. At the end of the compliance period, each firm receives additional allowances based on the actual output value in order to bring the total allowances per output value down to the specified benchmark or historical level emissions rate.

observations with annual change rates above ±500% are excluded. As a result, around 12.5% of firms are excluded during this process. (iv) The firms that entered the survey after 2011 are dropped because the matching procedure relies on firm covariates in 2009 and 2010. The firms that exited from the survey before 2012 are also removed from the sample since they do not have the post-treatment observations. Around 50.3% of total firms are removed from the sample. (v) We delete the firms without reported key variables in two consecutive years during our sample period of 2009-2015. Moreover, for a treated firm with missing data in one specific year, we search for a matched firm with the same data missing year during the matching procedure to ensure that the treatment and control units are as similar as possible in the remaining data pattern.[8] This round of cleaning excludes around 6.5% of firms in our sample. (vi) We remove observations with outlier values in key variables of interest (either greater than 99% or smaller than 1%). Finally, the cleaned dataset includes 280 regulated firms and 50,899 unregulated firms.

One concern is whether our data cleaning algorithm yields a biased sample. This concern is centered on whether these dropped missing values are affected by ETS-induced entry and exit. To test this, we count the number of dropped firms by region in each data cleaning step. Table S4 in the SI Appendix summarizes the results. First, we remove firms without pre-ETS observations (panel b). The number of firms removed in this step accounts for 43.5% of total removals for non-ETS regions and 44.5% for ETS regions. Second, we remove firms without post-ETS observations (panel c). The number of firms removed in this step accounts for 40.9% of total removals for non-ETS regions and 38.9% for ETS regions. Third, we remove firms without both pre- and post-ETS observations. The number of firms removed in this step accounts for 15.6% of total removals for non-ETS regions and 16.5% for ETS regions. Across the three steps of data cleaning, we do not

[8]Keeping firms that are observed for all sample periods, while deemed safer, tends to result in fewer samples appearing in our empirical analysis. This will be particularly true in our case because there exist missing observations in certain variables. Therefore, we choose the threshold for cleaning missing data (no missing observations in two consecutive years) that ensures the representativeness of our samples while not impairing the consecutiveness very much.

observe a dramatic difference in the removal ratios of firms between ETS and non-ETS regions. This suggests that ETS-induced entry and exit may not cause a concern of sample selection.

Table S5 reports the summary statistics. Column (1) reports the number of observations used in our analysis after matching. The last two columns show the means of each variable by treatment status. All variables except for turnover rate are in logarithms.

Moreover, we test alternative data cleaning algorithms. In our baseline model, we drop observations with annual growth or shrinkage above ±500% because the drastic changes might include unknown shocks or data entry errors. This threshold is set at the level where we can remove most of the potential bias due to the drastic changes while ensuring sample representativeness. To test the stability of our results, we also employ a stringent threshold of ±300% and a lenient threshold of ±700% in the data cleaning process as robustness checks. Table S7 shows the corresponding estimated ETS effects on carbon emissions. With a stringent cleaning algorithm, in columns (1) and (2), we observe some modest impacts of the ETS on emission intensity for the mass-based programs during the launching period. Columns (3) and (4) present the results with a lenient cleaning algorithm. We find robust evidence supporting the baseline conclusions.

3 Carbon Emission Measurement

Total carbon emissions in this paper consider both direct and indirect emissions. The former is from combustion of fossil fuels and the latter comes from consumption of purchased electricity. For each firm, we calculate carbon emissions by multiplying the consumption of each energy type (i.e., coal, oil, natural gas, and electricity) by its carbon emission factor. Energy consumption is measured in metric tons of standard coal equivalent (TCE).[9] Table S3 summarizes the emission factors for each energy type.

[9] 1 TCE is equivalent to 29,307 GJ

Besides energy-related emissions, those from industrial processes also need to be calculated (e.g., emissions from chemical reactions when producing chemicals, iron, steel, and cement) but require further information on manufacturing techniques and processes. Unfortunately, such information is not available in our dataset. As a robustness check, we drop the firms in the sectors that likely produce significant industrial process emissions, including iron and steel, chemical and petrochemical, cement, lime, glass, and other building materials sectors (IPCC, 2006). Table S8 presents the results. Overall, the main conclusions still hold.

4 Potential Confounding Policies

Threats to identification arise from the potential confounding environmental and energy policies that affect firms' carbon mitigation activities. Although provincial and industrial confounding policies are absorbed by the province and industry linear trends in the baseline model, we attempt to remove other confounding factors arising from overlapping policies. Our baseline estimates may be subject to additional potential confounding factors. Table S9 provides robustness checks.

First, time-variant provincial and industrial regulations may exist as confounders. To address this concern, we supplement the regression model with industry-year and province-year fixed effects. Columns (1) and (2) show the results. In Panel A, both estimates for the trading effects are negative and statistically significant for emissions but not for intensity. The trading effect is more pronounced for carbon emissions but remains muted for carbon intensity. In Panel B, the trading effects are negative and statistically significant at the 1% level, while the rate-based ETS effects remain positive and statistically significant at the 1% level. The inclusion of additional time-variant fixed effects does not change the overall baseline conclusions.

Second, we test the sensitivity against potential confounding environmental policies.

In 2011, the Ministry of Ecology and Environment targeted Beijing, Tianjin, and Hebei (BTH), one of the most polluted regions in China, to dramatically heighten air pollution regulations, especially for $PM_{2.5}$. Since CO_2 is co-emitted with many air pollutants, this regional air pollution control policy could also lead to the abatement of carbon emissions. To address this concern, we drop the firms from the BTH region in the robustness check. Columns (3) and (4) show the results. The main conclusion still holds. The ETS trading phase plays a substantial role in achieving the target of carbon mitigation. This effect mainly arises from those pilots using the mass-based ETS rule.

Lastly, some contemporaneous energy policies may also confound our estimates. In late 2011, the NDRC launched the Top 10,000 (Top-10k) Firm Energy Conservation Program, covering the top 10,000 energy users, accounting for around 60 percent of nationwide energy consumption in China. This central government-led program requires energy-intensive entities to meet the targets of energy conservation and technology upgrades with higher energy efficiency. Carbon emission activities of ETS firms were likely affected by this policy. In our samples, around 50% of ETS firms are included in this program. To address this concern while avoiding losing a large portion of observations, we add a policy indicator for Top-10k into the model as a robustness check. The last two columns in Table S9 present the results. The estimates for the Top-10k program are not statistically significant, indicating little impact on carbon mitigation for the firms in our sample. More importantly, the baseline conclusions on the trading effect still hold.

5 Alternative Matching Approaches

The literature lacks consensus about the inclusion variables and constraints in the matching process. A large number of included covariates and matching restrictions, while deemed safe, are likely to result in fewer matched pairs. Moreover, the performance of Mahalanobis distance-based matching is impaired when there are too many covariates

(Rubin, 1979; Zhao, 2004; Stuart, 2010). Therefore, we choose the variables (total emissions, emission intensity, and energy consumption) that determine a firm's regulatory status in a pilot region to ensure close similarity between the treated and control units while keeping the highest number of matched pairs. Besides, we restrict the matching within the same sector and year to control for the sector-specific time-variant factors that may affect both the treatment and control groups. Table S6 summarizes matching quality by comparing the sample means of covariates between the treatment and matched control groups. We find no significant differences between the two groups in any of the covariates used or even in those not used in the matching process. These results suggest that our matching strategy performs well in extracting reasonable comparison firms, similar to regulated firms within the same sector prior to the announcement of ETS.

The baseline model adopts a one-to-one nearest neighbor matching estimator. To ensure the stability of the main results, we consider a series of robustness checks, including alternative matching estimators, a rich set of covariates, and other matching approaches. First, we adopt nearest two and nearest five neighbor matching to increase the matched observations. Table S10 summarizes the estimation results. Columns (1)-(2) report the one-to-two matching results, and columns (3)-(4) report the one-to-five matching results. In all columns, the estimated coefficients for the announcement effect remain statistically insignificant. The estimates for the trading effect are negative and statistically significant at conventional levels. The baseline conclusions are not altered by accounting for different numbers of control units during the matching process.

Second, the baseline uses emissions, emissions per unit of output value, and energy consumption as the key covariates. We consider alternative covariates to select the control firms to match the characteristics of regulated firms prior to the ETS. Specifically, we account for eight additional sets of matching covariates, mixing among emissions, energy consumption, emission intensity, energy intensity, output, and sales. Table S11 reports the corresponding results. The estimated announcement effects are not statistically significant at any conventional level, while the estimated trading effects are negative and statistically significant. These results provide further corroborating support to the baseline conclusions.

Third, we consider three alternative matching approaches, i.e., propensity score matching (PSM), inverse probability of treatment weighting (IPTW), and coarsened exact matching (CEM). Table S12 presents the corresponding results. PSM is a widely used matching approach, which projects all covariates onto one scalar (i.e., propensity score). PSM can achieve a similar distribution of covariates between treated and control units while containing a higher dimension of information (Austin, 2011). But it also potentially increases model dependence and imbalance on matching variables (King and Nielsen, 2019). A similarly estimated scalar cannot effectively ensure similar values of each covariate used in matching. For robustness, a PSM-DID estimation is conducted. Columns (1) and (2) show the estimates. The results do not alter our baseline conclusions. One potential concern in our baseline is the loss of observations during the matching procedure. To address this, we use the IPTW method to transform the estimated propensity scores to weight firms (Hirano and Imbens, 2001), though this may cause large variance if the weights are extreme (Stuart, 2010). More specifically, each treated firm is weighted by $1/\hat{p}$ and each control firm is weighted by $1/(1-\hat{p})$, where $\hat{p}$ is the propensity score estimated from the matching procedure (Guadalupe, Kuzmina, and Thomas, 2012). As shown in columns (3) and (4), the results of the inverse probability of treatment weighting are consistent with our baseline results. Another popular approach is the CEM, which can achieve lower levels of imbalance and model dependence (King and Nielsen, 2019). But the proportion of matched units decreases rapidly with the number of strata, which may lead to a potentially larger bias in estimation (Azoulay, Graff Zivin, and Wang, 2010). Columns (5) and (6) show the corresponding estimates. The results are consistent with our baseline conclusions. Overall, these results suggest that our findings are robust to different matching approaches.

6 Heterogeneity: Electricity vs Manufacturing

We split the data by power generation and manufacturing industries and run the baseline regressions separately. Table S15 in the SI Appendix presents the results. The estimates for the manufacturing sector are consistent with the baseline results; however, the estimates for the power sector are statistically insignificant for both announcement and trading effects. This suggests that the estimated ETS effects in the baseline model are driven by the manufacturing sector. Please note that this result should be interpreted with caution. Our sample includes only 38 power plants regulated under the ETS, which may not provide adequate statistical power to identify the ETS effects on the electricity sector.

7 Heterogeneity: Allowance Allocation Rules

The classification of ETS pilots into a rate- or mass-based system is not unambiguous. To test the robustness, we provide four sets of alternative classifications for the ETS pilots. Table S13 presents the estimates.

First, the Guangdong ETS pilot differentiates allowance allocation methods in the electricity, cement, and steel sectors based on industrial processes.[10] However, we do not have further information to identify the specific industrial processes of each firm in our dataset. Moreover, the Chongqing ETS pilot allocates allowances based on self-declaration by covered firms and allows for ex-post adjustment at the end of the compliance period. This flexible and adjustable emission cap makes the Chongqing ETS pilot not precisely consistent with a mass-based allocation system. To address the ambiguities in the rate-based and mass-based classifications in these two ETS pilots, we drop all regulated firms from the Guangdong and Chongqing ETS pilots and their corresponding control firms.

[10]Power plants using cogeneration gensets, cement companies engaged in cement mining and other grinding processes, and steelmaking enterprises using a DR-EAR process (direct reduction using electric arc furnace) are granted allowances based on the emission-based grandfathering method (mass-based). Allowances of other firms in the electricity, cement, and steel sectors are allocated via the benchmarking method (rate-based).

Columns (1) and (2) show the estimation results. Overall, the baseline conclusions hold.

Second, the Guangdong and Hubei ETS pilots update allowances based on moving baseline periods of historical emissions across years. Unlike most mass-based ETS pilots, allocations in these two pilots are affected by firms' output choices in previous compliance periods and hence are endogenous to the firms. To further compare the difference of policy impacts between the output-based (endogenous) and non-output-based (exogenous) allocation methods, we categorize firms as endogenous and exogenous groups.[11] We define Endo_i as a binary indicator, equaling one if a firm is categorized into an endogenous group and zero otherwise. Based upon the allowance allocation model, we replace the variable Rate_i by Endo_i and rerun a variant of this model. Columns (3) and (4) show the policy effects between the endogenous and exogenous groups. The estimates for the interaction term between Trading and Endo are positive and statistically significant at the 1% level. These findings lend further support to the baseline conclusion. Under the rate-based and mass-based classification systems, we remove all mass-based firms under the output-based allocation (endogenous) regime because they are exceptional cases in the mass-based system. Columns (5) and (6) present the corresponding results. The estimates are positive and statistically significant, suggesting the stronger mitigation impacts of the mass-based rule over the alternative rate-based approach.

Third, the rate-based and mass-based allocations include both grandfathering and benchmarking rules.[12] The difference between grandfathering and benchmarking might blur the comparison of policy impacts between the rate-based and mass-based systems. To deal with this concern, we only compare the mass-based and rate-based systems for grandfathering.[13] Columns (7) and (8) show the results, which are consistent with the

[11]The pilots and sectors that use emission-based grandfathering with fixed baseline periods and benchmarking based on fixed historical production are classified as the exogenous method. Other pilots and sectors, which employ emission-based grandfathering with moving baseline periods, benchmarking based on moving historical production, intensity-based grandfathering, and benchmarking based on current production, are categorized as the endogenous method.

[12]The grandfathering rule determines allowances according to covered entities' historical levels, while the benchmarking rule allocates allowances based on sector- or technology-specific performance indicators.

[13]No pilots or sectors adopted the mass-based benchmarking method in China's ETS pilots. Hence, we

baseline conclusions.

Lastly, we have tried different model specifications by splitting samples into the mass-based and rate-based groups. Table S14 presents the estimates. Accounting for these alternative settings and classifications, we are reassured of the main conclusion that the ETS effects remain negative and statistically significant. More importantly, the rate-based ETS still achieves smaller carbon mitigation targets than the mass-based one.

cannot compare the effects between the mass-based and rate-based systems in benchmarking in our analysis.

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Supplementary Figures and Tables

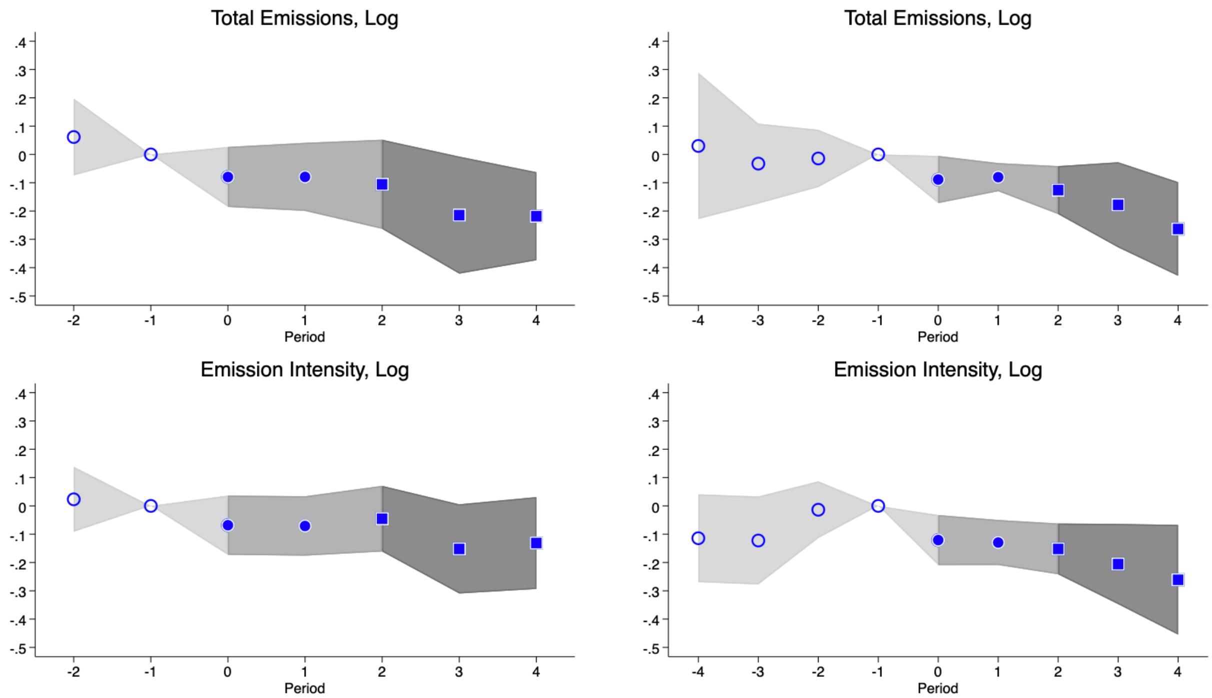

Figure S1: Dynamic Effects on Total Emissions and Emission Intensity

Notes: Left panel is based upon the period 2009-2015, the right panel is for the period 2007-2015. The shaded areas indicate the 95% confidence intervals. The hollow circles denote the point estimates for the pre-announcement effects, the solid circles indicate the announcement effects, and the rectangular symbol marks the trading effects.

Table S1: Covered Sectors across Regional ETS Pilots

Region	Announcement Year	Launch Year	Covered Sectors	Threshold	Emissions Covered
Beijing	2011	2013	Electricity, heating, cement, petrochemical, and other industries, large public buildings including hospitals, schools and governments	>10kt	40%
Shanghai	2011	2013	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textile, aviation, airports and ports, public and office buildings, railway stations	Industries>20kt; Non-industries>10kt	57%
Shenzhen	2011	2013	Electricity, building, manufacturing, water supply	Industries>5kt; Public buildings>20km^2 Office buildings>10km^2	40%
Guangdong	2011	2013	Electricity, cement, iron and steel, petrochemical industries, public services including hotels, restaurants and businesses	2013: >20kt; Since 2014: industries>10kt; non-industries>5kt	58%
Tianjin	2011	2013	Electricity, heating, iron and steel, chemical and petrochemical industries, oil and gas exploration	>20kt	60%
Hubei	2011	2014	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	energy consumption>60k tce	33%
Chongqing	2011	2014	Electricity, metallurgy, chemical industries, cement, iron and steel	>20kt	39.5%

Table S2: Allowance Allocation across Regional ETS Pilots

Region	Mass-based System				Rate-based System	
	Emission-based grandfathering, fixed baseline periods[1]	Emission-based grandfathering, moving baseline periods[2]	Fixed historical production based benchmarking[3]	Moving historical production based benchmarking[4]	Intensity-based grandfathering[5]	Current production based benchmarking[7]
	Exogenous	Endogenous (output-based)	Exogenous	Endogenous (output-based)	Endogenous (output-based)	Endogenous (output-based)
EU ETS	Phases I and II		Phase III	Emission-intensive and trade-exposed industries (Phase III)		
California C&T				Industrial facilities		
Beijing	Cement, petrochemical and other industries, large public buildings including hospitals, schools and governments.				Electricity, heating	
Shanghai	Iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textiles, public and office buildings, railway stations					Electricity, aviation, airports and ports.
Shenzhen					Manufacturing	Electricity, heating, building, water supply.
Guangdong[7]		Electricity (cogeneration genset), cement (cement mining and other grinding process), steel (DR-EAF route), petrochemical industries.				Electricity (pure genset), cement (cement clinker production and cement grinding process), steel (BF-BOF route).
Tianjin	Iron and steel, chemical and petrochemical industries, oil and gas exploration.				Electricity, heating	
Hubei		Metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement (only 2014), medicine and pharmacy, food and beverage, paper making.				Electricity, heating, cement (only 2015).
Chongqing[8]		Electricity, metallurgy, chemical industries, cement, iron and steel (due to self-declaration & ex-post adjustment).				

Notes: 1. Emission-based grandfathering with fixed baseline periods, known as "pure grandfathering", depends on firm's historical emission level in fixed periods to compute the number of allowances.
2. Since the baseline periods of a firm's historical emissions are moving, the number of allowances is updated based on outputs across periods and therefore categorized as "output-based" allocation.
3. Allowance = sectoral benchmark × firms' historical production in fixed baseline periods.
4. Allowance = sectoral benchmark × firms' historical production in moving baseline periods. Hence, the number of allowances is updated based on output values across periods and categorized as "output-based" allocation.
5. Intensity-based grandfathering depends on a firm's historical emission intensity level and firm's current output level to compute the number of allowances.
6. Allowance = sectoral benchmark × firms' current production level.
7. The Guangdong pilot determines allowance allocation methods based on industrial processes and techniques in the electricity, cement, and steel sectors.
8. The Chongqing pilot allocates allowances on the basis of the self-declaration number by covered firms and allows for ex-post adjustment of the allowance number at the end of the compliance period.

Table S3: China's CO_2 Emission Factors

Energy	Unit	Emission Factor
Panel A: Emission Factors of Coal, Oil and Natural Gas		
Coal	$kgCO_2/kg$	1.978
Oil	$kgCO_2/kg$	3.065
Natural Gas	$kgCO_2/m^3$	1.809
Panel B: Emission Factors of Electricity		
North China Grid	$kgCO_2/kWh$	0.8843
Northeast China Grid	$kgCO_2/kWh$	0.7769
East China Grid	$kgCO_2/kWh$	0.7035
Central China Grid	$kgCO_2/kWh$	0.5257
Northwest China Grid	$kgCO_2/kWh$	0.6671
China Southern Power Grid	$kgCO_2/kWh$	0.5271

Notes: China has six regional power grids whose carbon emission factors are computed separately. The North China Grid covers Beijing, Tianjin, Hebei, Shandong, Shanxi,and Inner Mongolia. The Northeast China Grid covers Liaoning, Jilin, and Heilongjiang. The East China Grid covers Shanghai, Jiangsu, Zhejiang, Anhui, and Fujian. The Central China Grid covers Henan, Hubei, Hunan, Jiangxi, Chongqing, and Sichuan. The Northwest China Grid Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The China Southern Power Grid covers Guangdong, Guangxi, Yunnan, Guizhou, and Hainan.
Source of Panel A: Department of Energy Statistics, National Bureau of Statistics of China and IPCC Guidelines for National Greenhouse Gas Inventories.
Source of Panel B: National Center for Climate Change Strategy and International Cooperation, National Development and Reform Comission of China.

Table S4: Number of Removed Firms due to No Pre- or Post-ETS Observations

	Non-ETS Regions (1)	ETS Regions (2)	Difference (3) = (2) - (1)
a. # of removed firms (row a = b + c + d)	312,311	79,049	
b. # of removed firms due to no pre-ETS data	135,821	35,215	
ratio of removed firms (row b/row a)	43.5%	44.5%	-1%
c. # of removed firms due to no post-ETS data	127,635	30,770	
ratio of removed firms (row c/row a)	40.9%	38.9%	2%
d. # of removed firms due to no pre- & post-ETS data	48,855	13,064	
ratio of removed firms (row d/row a)	15.6%	16.5%	-0.9%

Notes: Row a shows the total number of removed firms that do not have observations before the announcement or after the trading of the ETS. Row b represents the number of firms that enter the survey after the announcement period. Row c stands for the number of firms that exit the survey before trading. Row d records the number of removed firms that enter the survey after the announcement but exit it before trading.

Table S5: Summary Statistics

Variables	N	Mean	Std	Mean	
				NonETS	ETS
Panel A. Firm-level Carbon Emissions and Energy Consumption					
Emission	2,428	11.06	2.525	11.07	11.06
Emission/Output	2,428	0.222	2.263	0.208	0.236
Energy Consumption	2,428	9.802	2.684	9.785	9.820
Energy/Output	2,428	-1.038	2.434	-1.075	-0.999
Panel B. Firm-level Attributes					
Output Value	2,428	10.84	1.116	10.86	10.82
Sale	2,428	10.91	1.109	10.92	10.91
Labor	2,428	6.505	0.980	6.498	6.512
Wage	2,397	7.989	1.180	7.901	8.080
Wage/Labor	2,397	1.487	0.816	1.403	1.574
Capital	2,295	9.912	1.462	9.864	9.963
Value Added	2,317	9.165	1.302	9.157	9.173
Export	2,428	4.385	4.909	4.237	4.537
Invest	1,833	6.865	1.968	6.847	6.885
Total Factor Productivity	2,185	-0.595	1.479	-0.592	-0.598
Capital/Labor	2,295	3.402	1.624	3.369	3.435
Output/Labor	2,428	4.335	1.134	4.361	4.307
Output/Capital	2,295	0.918	1.044	0.996	0.836
Panel C. Regional Carbon Market Performance					
Carbon Price	2,428	0.739	1.528	0.000	1.500
Turnover Rate	2,428	0.004	0.011	0.000	0.007

Notes: Panels A and B report firm-level carbon emissions and attributes, respectively. Panel C shows regional carbon market performance. Units: Emission - metric tons of CO_2; Energy Consumption - metric tons of standard coal equivalent (TCE), with 1 TCE = 29,307 GJ; Output Value, Sale, Wage, Capital, Value Added, Export, Invest - ten thousands of Yuan; Labor - number of employees; Carbon Price - Yuan (1 Yuan = 0.145 Dollars). All variables are in natural logarithms except Turnover Rate. Turnover Rate is the ratio of trading volume to the total allowance in each carbon market.

Table S6: Balancing Test

	Unmatched Sample			Matched Sample		
	280 treated vs 50,899 control firms			198 treated vs 198 control firms		
Variables	Treated (1)	Control (2)	P-value (3)	Treated (4)	Control (5)	P-value (6)
Panel A: Covariates Used in Matching						
Emission 2010	11.180	7.194	0.000	11.197	11.204	0.978
Emission/Output 2010	0.330	-1.308	0.000	0.368	0.360	0.973
Energy Consumption 2010	9.906	7.873	0.000	9.914	9.910	0.988
Emission 2009	10.949	7.820	0.000	10.811	10.771	0.888
Emission/Output 2009	0.325	-1.253	0.000	0.302	0.276	0.918
Energy Consumption 2009	9.639	8.132	0.000	9.500	9.457	0.891
Panel B: Covariates Not Used in Matching						
Output Value 2010	10.850	8.502	0.000	10.829	10.844	0.894
Sale 2010	10.923	8.547	0.000	10.901	10.894	0.946
Energy/Output 2010	-0.944	-2.127	0.000	-0.915	-0.934	0.941
Labor 2010	6.552	4.990	0.000	6.551	6.512	0.697
Wage 2010	7.985	7.130	0.000	7.998	7.820	0.091
Capital 2010	9.992	6.978	0.000	10.006	9.885	0.434
ValueAdded 2010	9.199	6.651	0.000	9.182	9.134	0.717
Invest 2010	7.006	4.714	0.000	7.018	6.952	0.785
Output Value 2009	10.624	9.073	0.000	10.509	10.494	0.909
Sale 2009	10.652	9.082	0.000	10.543	10.504	0.764
Energy/Output 2009	-0.985	-1.824	0.000	-1.009	-1.037	0.919
Labor 2009	6.586	5.502	0.000	6.560	6.455	0.366
Wage 2009	7.737	7.037	0.000	7.688	7.527	0.193
Capital 2009	9.894	7.779	0.000	9.809	9.616	0.282
ValueAdded 2009	8.890	7.251	0.000	8.767	8.738	0.854
Invest 2009	7.135	5.267	0.000	7.008	7.058	0.838

Notes: All firm-level attributes used in the matching approach are historical records in 2009 and 2010 during the pre-announcement phase. All attributes are in natural logarithms.

Table S7: Robustness Checks on Alternative Data Cleaning Algorithms

VARIABLES	Growth Rate < ±300%		Growth Rate < ±700%	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)
Panel A: Main Effects				
Announcement	-0.012	0.077	-0.147***	-0.101
	(0.090)	(0.081)	(0.052)	(0.084)
Trading	-0.073	0.022	-0.145***	-0.094**
	(0.063)	(0.055)	(0.040)	(0.041)
R-squared	0.255	0.263	0.202	0.209
Panel B: Main Effects by Rate- and Mass-based ETS				
Announcement	-0.038	0.052	-0.182***	-0.150*
	(0.081)	(0.072)	(0.045)	(0.080)
Trading	-0.298	-0.171**	-0.357***	-0.402***
	(0.175)	(0.080)	(0.122)	(0.076)
Trading×Rate	0.274	0.232**	0.256**	0.370***
	(0.166)	(0.098)	(0.114)	(0.080)
R-squared	0.262	0.268	0.206	0.215
Observations	1,942	1,942	2,670	2,670
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S8: Robustness Checks on Alternative Emission Measurements

VARIABLES	Total Emissions (1)	Emission Intensity (2)
	Panel A: Main Effects	
Announcement	-0.113	-0.031
	(0.068)	(0.072)
Trading	-0.152***	-0.059
	(0.051)	(0.062)
R-squared	0.224	0.261
	Panel B: Main Effects by Rate- and Mass-based ETS	
Announcement	-0.144**	-0.066
	(0.067)	(0.074)
Trading	-0.491**	-0.474***
	(0.192)	(0.126)
Trading×Rate	0.372*	0.455***
	(0.184)	(0.097)
R-squared	0.226	0.219
Observations	1,530	1,530
Firm FE	Y	Y
Year FE	Y	Y
Province Trend	Y	Y
Industry Trend	Y	Y

Notes: We exclude those sectors with significant emissions from industrial process (iron and steel, chemical and petrochemical, cement, lime, glass and other building materials sectors). All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S9: Robustness Checks on Confounding Factors

VARIABLES	Additional FE		Without BTH		Top-10k	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main Effects						
Announcement			-0.087	-0.007	-0.088	-0.017
			(0.067)	(0.084)	(0.073)	(0.083)
Trading	-0.190***	-0.069	-0.132**	-0.033	-0.166***	-0.097*
	(0.042)	(0.056)	(0.050)	(0.046)	(0.046)	(0.052)
Top-10k					-0.007	0.026
					(0.059)	(0.045)
R-squared	0.222	0.239	0.197	0.212	0.198	0.220
Panel B: Main Effects by Rate- and Mass-based ETS						
Announcement			-0.118*	-0.063	-0.120*	-0.069
			(0.068)	(0.076)	(0.064)	(0.072)
Trading	-0.474***	-0.408***	-0.333**	-0.378***	-0.400**	-0.439***
	(0.103)	(0.090)	(0.138)	(0.076)	(0.149)	(0.097)
Trading×Rate	0.331***	0.382***	0.230*	0.403***	0.286*	0.417***
	(0.086)	(0.077)	(0.120)	(0.069)	(0.143)	(0.086)
Top-10k					0.016	0.042
					(0.054)	(0.038)
R-squared	0.206	0.233	0.204	0.226	0.207	0.233
Observations	2,402	2,402	2,188	2,188	2,416	2,416
Firm FE	Y	Y	Y	Y	Y	Y
Year FE			Y	Y	Y	Y
Province Trend			Y	Y	Y	Y
Industry Trend			Y	Y	Y	Y
Province-Year FE	Y	Y				
Industry-Year FE	Y	Y				

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. "Without BTH" refers to the removal of observations located in Beijing, Tianjin, and Hebei areas due to the confounding local environmental policy. Top-10k equals one for firms under the Top 10k Energy Conservation Program. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S10: Robustness Checks on Alternative Matching Numbers

VARIABLES	1:2 Matching (198 treated vs 396 control)		1:5 Matching (198 treated vs 990 control)	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)
Announcement	-0.051	0.038	-0.071	-0.004
	(0.066)	(0.067)	(0.049)	(0.032)
Trading	-0.126***	-0.101*	-0.122***	-0.102***
	(0.042)	(0.049)	(0.035)	(0.034)
Observations	3,668	3,668	6,501	6,501
R-squared	0.154	0.185	0.115	0.127
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S11: Robustness Checks on Alternative Sets of Covariates in Mahalanobis Matching

VARIABLES	Covariate Set 1 (176 treated vs 176 control)		Covariate Set 2 (169 treated vs 169 control)		Covariate Set 3 (195 treated vs 195 control)		Covariate Set 4 (210 treated vs 210 control)	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)	Total Emissions (5)	Emission Intensity (6)	Total Emissions (7)	Emission Intensity (8)
Announcement	0.012	-0.008	-0.121	-0.085	-0.071	-0.024	-0.032	0.030
	(0.070)	(0.093)	(0.081)	(0.093)	(0.081)	(0.094)	(0.048)	(0.070)
Trading	-0.028	-0.107*	-0.182***	-0.185***	-0.153***	-0.110**	-0.132**	-0.099*
	(0.037)	(0.053)	(0.040)	(0.049)	(0.045)	(0.048)	(0.057)	(0.056)
Observations	2,088	2,088	1,983	1,983	2,381	2,381	2,575	2,575
R-squared	0.211	0.236	0.255	0.249	0.202	0.218	0.177	0.217
	Covariate Set 5 (193 treated vs 193 control)		Covariate Set 6 (202 treated vs 202 control)		Covariate Set 7 (180 treated vs 180 control)		Covariate Set 8 (173 treated vs 173 control)	
Announcement	-0.050	0.004	-0.046	0.016	-0.081	-0.091	-0.077	-0.047
	(0.048)	(0.067)	(0.066)	(0.089)	(0.063)	(0.096)	(0.048)	(0.062)
Trading	-0.174***	-0.156***	-0.138**	-0.103*	-0.148***	-0.157**	-0.184***	-0.200***
	(0.046)	(0.040)	(0.053)	(0.057)	(0.044)	(0.056)	(0.043)	(0.060)
Observations	2,336	2,336	2,475	2,475	2,141	2,141	2,050	2,050
R-squared	0.206	0.209	0.195	0.235	0.223	0.250	0.230	0.246
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). A set of covariates used in the matching process vary across columns. Covariate Set 1: emissions, emissions per output, energy consumption, and energy per output. Set 2: emissions, emissions per output, energy consumption, and sale. Set 3: emissions, energy consumption and output. Set 4: emissions, emissions per output, output. Set 5: emissions, energy consumption, sale. Set 6: emissions, energy consumption, energy per output. Set 7: emissions, emissions per output, energy consumption, output. Set 8: emissions, energy consumption, energy per output, sale. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S12: Robustness Checks on Alternative Matching Methods

VARIABLES	PSM (220 treated vs 220 control)		IPTW (280 treated vs 50,899 control)		CEM (149 treated vs 149 control)	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement	-0.136**	-0.095*	-0.053	-0.028	-0.036	0.030
	(0.050)	(0.052)	(0.034)	(0.033)	(0.059)	(0.084)
Trading	-0.159**	-0.070**	-0.141***	-0.068*	-0.195**	-0.119**
	(0.059)	(0.034)	(0.033)	(0.035)	(0.066)	(0.056)
Observations	2,715	2,715	254,378	254,378	1,742	1,742
R-squared	0.174	0.210	0.379	0.347	0.205	0.235
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y

Notes: PSM - propensity score matching; IPTW - inverse probability of treatment weighting; CEM - coarsened exact matching. All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S13: Robustness Checks on Alternative Classifications for Rate-based Allowance Allocation

VARIABLES	Alt. Classification 1 drop GD&CQ		Alt. Classification 2 exogenous & endogenous		Alt. Classification 3 drop mass-based endogenous		Alt. Classification 4 only grandfathering	
	Total Emissions (1)	Emission Intensity (2)	Total Emissions (3)	Emission Intensity (4)	Total Emissions (5)	Emission Intensity (6)	Total Emissions (7)	Emission Intensity (8)
Announcement	-0.126	-0.073	-0.103	-0.047	-0.221***	-0.136*	-0.090	-0.023
	(0.076)	(0.079)	(0.067)	(0.075)	(0.062)	(0.074)	(0.074)	(0.077)
Trading	-0.546***	-0.571***	-0.538***	-0.542***	-0.634***	-0.676***	-0.400***	-0.426***
	(0.147)	(0.113)	(0.169)	(0.102)	(0.177)	(0.104)	(0.123)	(0.104)
Trading×Rate	0.427***	0.552***			0.516***	0.650***	0.263*	0.410***
	(0.147)	(0.102)			(0.171)	(0.091)	(0.127)	(0.113)
Trading×Endo			0.426**	0.512***				
			(0.160)	(0.097)				
Observations	1,727	1,727	2,416	2,416	2,008	2,008	1,865	1,865
R-squared	0.234	0.273	0.205	0.232	0.227	0.263	0.224	0.251
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Endo equals one if the regulated firms are categorized into the endogenous rate-based system. Columns (1) and (2) drop all regulated firms in Guangdong (GD) and Chongqing (CQ) ETS pilots and their corresponding control firms. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S14: Alternative Model Specification on Rate-based vs. Mass-based Allocation

VARIABLES	Total Emissions			Emission Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
Announcement	0.029	-0.238***	-0.118*	-0.083	-0.069	-0.049
	(0.127)	(0.082)	(0.062)	(0.204)	(0.085)	(0.073)
Trading×Mass	-0.266		-0.389***	-0.428***		-0.326***
	(0.167)		(0.120)	(0.113)		(0.097)
Trading×Rate		-0.115*	-0.117**		-0.018	-0.044
		(0.057)	(0.054)		(0.049)	(0.049)
Observations	674	1,758	2,416	674	1,758	2,416
R-squared	0.447	0.237	0.207	0.398	0.270	0.227
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y	Y	Y
IndustryTrend	Y	Y	Y	Y	Y	Y
Subsamples	Mass-based	Rate-based	Full	Mass-based	Rate-based	Full

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Mass equals one if the regulated firms are categorized into the mass-based group. Rate equals one if the regulated firms are categorized into the rate-based group. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S15: Heterogeneity of ETS Effects by Sectors

VARIABLES	Electricity Sector		Manufacturing Sector	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)
Announcement	-0.044	-0.006	-0.047	0.018
	(0.229)	(0.178)	(0.064)	(0.069)
Trading	-0.003	0.014	-0.187***	-0.097*
	(0.172)	(0.192)	(0.037)	(0.055)
Observations	427	427	1,977	1,977
R-squared	0.342	0.329	0.207	0.232
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table S16: Policy Heterogeneity based upon Observable Carbon Market Performance

VARIABLES	Carbon Price		Turnover Rates	
	Total Emissions	Emission Intensity	Total Emissions	Emission Intensity
	(1)	(2)	(3)	(4)
Announcement	-0.111*	-0.044	-0.075	-0.028
	(0.056)	(0.069)	(0.066)	(0.065)
Carbon Price	-0.114***	-0.096***		
	(0.034)	(0.028)		
Turnover Rate			-7.403**	-7.167*
			(2.926)	(3.490)
Carbon Price×Rate	0.083**	0.086***		
	(0.029)	(0.025)		
Turnover Rate×Rate			4.613*	6.007*
			(2.706)	(3.333)
Observations	2,416	2,416	2,416	2,416
R-squared	0.208	0.227	0.200	0.223
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y
Industry Trend	Y	Y	Y	Y

Notes: All dependent variables are in natural logarithms. Announcement equals one for the regulated firms during the announcement period (2011-2012). Trading equals one for the regulated firms during the trading period (2013-2015). Rate equals one if the regulated firms are categorized into the rate-based group. Carbon price and turnover rate are only available for the regulated firms during the trading period (2013-2015); zero otherwise. Standard errors in parentheses are clustered at the industry level. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.