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How Do Carbon Taxes Affect Emissions? Plant-Level Evidence from Manufacturing

Younes Ahmadi[1] · Akio Yamazaki[1,2] · Philippe Kabore[3]

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Abstract

This paper investigates how carbon taxes affect emissions by examining British Columbia's revenue-neutral carbon tax in the manufacturing sector. We theoretically demonstrate that carbon taxes can achieve emission reductions while increasing production. Recycling carbon tax revenues to lower corporate income tax rates encourages investments, allowing plants to emit less per unit of output. Using detailed confidential plant-level data, we evaluate this theoretical prediction by exploiting the treatment intensity through plants' emission intensity. We find that the carbon tax lowers emissions by 4 percent. Furthermore, we find that the policy had a positive output effect and negative emission intensity effect, suggesting that the carbon tax encouraged plants to produce more with less energy. We provide initial evidence showing how a revenue-neutral carbon tax may achieve emission reductions while stimulating the economy.

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✉ Akio Yamazaki
a-yamazaki@grips.ac.jp

Younes Ahmadi
yahmadi@ucalgary.ca

Philippe Kabore
pkabo048@uottawa.ca

[1] Department of Economics, University of Calgary, Calgary, AB, Canada

[2] National Graduate Institute for Policy Studies (GRIPS), Tokyo, Japan

[3] Department of Economics, University of Ottawa, Ottawa, ON, Canada

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1 Introduction

At the 21st Conference of Parties[1] in Paris (December 2015), countries, by consensus, adopted the first universal climate agreement to tackle global warming. Several countries have already implemented carbon pricing policies to reduce their greenhouse gas (GHG) emissions.[2] After the Paris agreement, there is a general expectation in the international community that these policies would be expanded. Many countries are now proposing to achieve the net-zero emissions by 2050 through more ambitious climate action plans, including carbon pricing. Theoretical models show that a uniform carbon tax is an effective tool to achieve emission reduction targets at the lowest economic costs.[3] However, the political feasibility of the policy is still heavily debated among policymakers and the public because of its potential adverse effects on the economy. Some even argue that the current carbon prices around the world are set too low to reach emission reduction targets.[4] For many countries to achieve the net-zero emission goal, it is essential to understand the effectiveness of carbon-pricing policies in reducing emissions. Thus this paper takes advantage of a unique plant-level dataset to investigate the effect of the carbon tax, implemented by British Columbia (BC) in 2008, on GHG emissions from manufacturing plants.

The carbon tax in BC was unexpectedly announced in February 2008 and has been in effect since July 2008. The tax rate initially began at \$10 per tonne of CO_2 equivalent (CO_2 eq) and increased by \$5 annually, reaching \$30 in 2012. The tax applies to all fossil fuels purchased within BC and covers 77% of provincial emissions (Harrison 2012). There are three reasons why this policy is ideal for estimating the causal effect of a carbon tax on GHG emissions. First, the tax is comprehensive, applying to all fossil fuels purchased by all plants within BC. Second, its tax rate is high compared to other existing carbon policies, so companies are more likely to change their behavior in response to the policy.[5] Third, the fact that the tax was introduced shortly after its unexpected announcement eliminates any

[1] Conference of Parties is the formal annual meeting of the United Nations Framework Convention on Climate Change (UNFCCC) Parties. In these meetings, the member countries assess countries' progress in reducing greenhouse gas emissions and negotiate climate change agreements.

[2] There are 64 carbon pricing policies implemented worldwide, and the price ranges from less than \$1 (Poland) to \$137 (Sweden). See World Bank (2021) for mode details. In fact, Canada is now proposing to increase the federal carbon price to \$170 by 2030. See https://www.cbc.ca/news/politics/carbon-tax-hike-new-climate-plan-1.5837709

[3] A uniform carbon tax is a per-unit charge on fossil fuels based on their carbon embodiment, applied to all consumers at the same rate. The effect of a carbon tax on GHG emissions is less pronounced when the carbon tax is revenue neutral (i.e., all the tax revenues from the policy are returned to consumers to maintain the government revenues constant). Theoretical models show that the effect depends on how the tax revenue is recycled.

[4] Pretis (2020) shows no identifiable aggregate emission response from British Columbia's carbon tax.

[5] Québec was the first province to introduce a carbon tax, but the tax rate is only around \$3 per tonne of CO_2eq and does not include all emitters. Some Scandinavian countries have carbon taxes as high as \$150. However, the effective tax rates are smaller due to many tax exemptions, and in some cases, the energy excise taxes were removed and replaced by carbon taxes.

anticipatory effects (i.e., actions prior to the implementation of the policy) as plants presumably did not have enough time to adjust their behavior.

Our empirical strategy is motivated by a simple model of monopolistic competition with heterogeneous plants exposed to a carbon tax, which is borrowed from Yamazaki (2022). We start by decomposing the plant-level emission responses into scale effect and technique effect.[6] By allowing plants to invest in energy-saving technologies, we theoretically show that carbon taxes can reduce emissions while producing more. This is possible through recycling tax revenues from the carbon tax to lower the corporate income tax (CIT) rates. The carbon tax alone would reduce emissions at the cost of output (i.e., negative scale effect), while the CIT reduction would ameliorate the distortion in the capital market and encourage plants to be more efficient in both energy consumption and production (i.e., positive technique effect).

We further show that the magnitude of emission responses increases monotonically with plants' emission intensity. Therefore, it is reasonable to assume that high emission-intensive plants are more affected by the carbon tax than low emission-intensive plants. Using the theoretical insights, we design a difference-in-differences (DID) estimator allowing for differential treatment intensity. We use plant-level emission intensity as a measure of exposure to the carbon tax. As the magnitude of plants' exposure to the carbon tax monotonically increases with their emission intensity. We contend that plants with high emission intensity are more likely to respond to the policy by adjusting their operation or production technologies than the low emission-intensive plants. Our augmented DID estimator compares changes in emission differences between high emission-intensive and low emission-intensive plants in BC with changes in the same emission differences in the rest of Canada before and after the unilateral implementation of the carbon tax.[7] Our estimator identifies the relative emission responses between the high and low emission-intensive plants. Furthermore, we exploit the panel structure of the data by including various fixed effects to control for possible unobserved confounding factors, such as commodity price shocks, provincial geographic characteristics, and industry factor intensities.

We estimate the emission effect of the policy using the confidential plant-level manufacturing dataset, the Annual Survey of Manufacturing (ASM). This dataset consists of detailed information on plant-level manufacturing activities, such as fuel expenditures, total sales, and employment. What is unique about this dataset is that having access to plant-level fuel expenditures allows us to construct the most comprehensive plant-level GHG emission dataset for Canada.[8] Manufacturing sector accounts for a relatively small

[6] Antweiler et al. (2001) refer to the emission response by increasing the production size as scale effect while referring to the emission response by changing the production technology that improves emissions per unit of output as technique effect.

[7] Some, such as Andersson (2019), argue that the carbon tax may have a general equilibrium effect and lead to carbon leakages into other provinces, violating the stable unit treatment value assumption. To minimize this concern, we also estimate the emission effect using only provinces that have very low trade flows with BC because we expect very limited carbon leakages into these provinces. The selected provinces are Newfoundland and Labrador, Prince Edward Island, Nova Scotia, New Brunswick, Manitoba, and Saskatchewan. The baseline estimation results are robust to this sample difference. The results are presented in Table 11 in Appendix B.

[8] Alternatively, one can use the facility-level emission data available at Environment Canada, known as Greenhouse Gas Reporting Program (GHGRP). This data includes only large industrial emitters that emit more than 100 kilotonnes per year. The reporting threshold was reduced to 50 kilotonnes in 2009 and further to 10 kilotonnes in 2018. We believe that our data is better suited as it covers all manufacturing plants and provides more variation, while the facility-level emission data only covers the large facilities.

portion of BC's total emissions; however, there are three reasons why focusing on this sector provides valuable insights about the effectiveness of carbon taxes. First, while limited to manufacturing plants, the ASM dataset allows us to calculate plant-level emissions and emission intensity while other publicly available datasets cannot. Second, manufacturing plants in BC are relatively emission-intensive, making this sector more likely to respond to the policy than other sectors. Third, a large variation in the emission intensity of manufacturing plants allows us to capture an extra source of variation across plants and design a more credible estimation strategy.

We find that the BC carbon tax lowered GHG emissions. The point estimate shows a statistically significant reduction in emissions by 4 percent.[9] Furthermore, we show that the policy increased outputs, suggesting that the carbon tax provided enough incentives for plants to take actions to produce more with less (fossil-fuel) energy. Our findings are quite appealing, especially to policymakers, because implementing a carbon tax could both reduce emissions and strengthen the economy.

There are potentially two factors that may contribute to the increased outputs. First, the amount of money the BC government returned to the economy was about 15% more than what the carbon tax collected in all years between 2008 and 2016 (e.g., the BC carbon tax raised \$1.2 billion in 2012-13 and returned \$1.4 billion). This is mainly because the BC government announced the reduction of personal and CIT rates based on the projected carbon revenue, and the actual revenue was less than the projected revenue. This means that the BC economy received a net reduction in taxes. Second, the revenue recycling feature of the policy may have played an important role in generating the positive output effect. The revenues collected from the carbon tax were used to lower the rates of corporate and personal income taxes. Theoretically, a reduction of the CIT rate increases investments and capital formation, resulting in lower emission intensity and higher output. As emission-intensive plants in BC are more capital intensive, these plants receive larger benefits from the CIT cut relative to the low-emission-intensive plants. Therefore, the output of high emission-intensive plants could increase, and their emission intensity could decrease relative to the low emission-intensive plants. This argument is consistent with the results found in our paper. Yamazaki (2017, 2022) has a similar argument regarding the importance of the revenue recycling feature of the BC carbon tax, and our results are consistent with their findings.[10]

In addition to the plant-level emission responses, we adapt an approach developed by Najjar and Cherniwchan (2021) to decompose the aggregate emission response into the scale, technique, and selection effects.[11] This allows us to discuss the aggregate implications by using the point estimates for the scale, technique, and selection effects in this paper. We find that the aggregate manufacturing emission decline in response to the policy. This decomposition exercise illustrates that a reduction in aggregate emissions would be mainly a result of the scale and technique effects. The size of the selection effect is limited,

[9] We also find considerable heterogeneity in emission responses to the policy across plants with different characteristics, such as plant size, ownership types, and trade intensity. For example, singly-owned plants are affected more negatively than multi-plant firms' plants.

[10] Yamazaki (2017) also argues that there is a positive demand effect from lowering the personal income tax, which could also help to explain the positive output effect found in this paper.

[11] Najjar and Cherniwchan (2021) refer selection effect to be the change in aggregate emission through plant entries and exits.

suggesting that the emission responses to the policy are dominated by the intensive margin adjustments of the surviving plants.

A large number of studies examine the effect of carbon taxes on GHG emissions using simulation methods, such as Manne et al. (1990), Goto (1995), Floros and Vlachou (2005), and Wissema and Dellink (2007). Although they find that a uniform carbon tax would lead to a significant reduction in GHG emissions, it is difficult to solely rely on these findings for designing future policies. What we need is more of evidence-based policy suggestions.

The empirical findings, thus far, from ex-post analyses are limited and concentrated on the aggregate emission responses to carbon taxes.[12] For instance, Bohlin (1998) and Andersson (2019) both investigate the effect of the Swedish carbon tax, implemented in 1991. Bohlin finds that the transportation sector was not affected, and emissions from industrial sectors increased due to exemptions that decreased the effectiveness of the policy. It, however, finds that GHG emissions declined in the heating sector as a result of substitution from coal to biofuel. On the other hand, Andersson uses a synthetic control method and finds that transportation emissions declined by 11 percent. Lin and Li (2011) use a DID method to estimate the emission effect of carbon taxes in Scandinavian countries and the Netherlands. They find that there was no significant effect in Denmark, Sweden, and the Netherlands, and that the carbon tax in Norway led to a substantial increase in GHG emissions from the oil and gas sector due to tax exemptions. This paper provides new evidence to this literature by examining the micro-level responses to a carbon tax.

This paper is closely related to Metcalf (2019) and Pretis (2020) as they both investigated the aggregate emission response to the BC carbon tax. Metcalf finds that the BC carbon tax reduced aggregate emissions between 5 and 8 percent, although the estimates are sensitive to the specifications. Pretis shows that the results of Metcalf (2019) are not robust and finds that the BC carbon tax did not have a (statistically) significant effect on aggregate emissions. It further investigates the emission effects for six sectors and finds that emissions from the transportation sector declined.[13] The paper concludes that the carbon tax rate was too low for the policy to have any impacts. Pretis (2020)'s inability to detect a (statistically) significant emission reduction for the industrial sector may be that the industrial sector consists of a mix of many subsectors with different emission intensity, possibly suffering from the aggregation bias. We address this issue by utilizing the micro-level data to directly observe the plant-level emission intensity in the manufacturing sector and employ the augmented DID estimation.

Lastly, this paper provides theoretical predictions of emission responses from carbon taxes. We do so by adapting the model of Yamazaki (2022). Yamazaki theoretically shows that carbon taxes can increase manufacturing productivity by recycling tax revenues to reduce CIT rates. It allows plants to invest in energy-saving technologies and explicitly models the plant-level responses from both the carbon tax and the revenue recycling through the CIT reduction. The paper finds that the BC carbon tax negatively affects productivity while the CIT reduction increases it, offsetting the negative carbon tax effect. We extend the model of Yamazaki (2022) to show how the carbon tax affects plant-level emissions through output and emission intensity responses. Although not tested, we further

[12] There are considerable numbers of ex-post analyses investigating cap-and-trade policies, such as the European Union Emissions Trading System (see Martin et al. (2016) for a review) and US Regional Greenhouse Gas Initiative (e.g., Fell and Maniloff (2018)).

[13] It also shows that the industrial emissions, including manufacturing, declined but its point estimate was not statistically different from zero.

emphasize the importance of the revenue recycling feature of the policy on plant-level emission responses.

The remainder of the paper is organized as follows. Section 2 provides an overview of the BC carbon tax and its features. Section 3 presents the theoretical framework. The description of the data and empirical methodology are presented in Sect. 4. Section 5 presents the estimation results and robustness checks. Section 6 discusses the aggregate implications of our plant-level estimates. Section 7 concludes. The results of additional empirical analyses, and additional tables and figures regarding the data are reported in Appendix.

2 Overview of the BC Carbon Tax

The BC's Liberal government announced the new climate policy agenda in its throne speech in February 2008. The target of the policy was to reduce BC's GHG emissions by 33 percent (i.e., 10 percent below the 1990 level) by 2020. Additionally, all electricity generators were required to have zero emissions by 2016. Two months after the throne speech, the BC government announced its intention to join five U.S. states in developing a regional cap and trade system called the Western Climate Initiative. This announcement was completely unexpected because the Liberal government had been previously criticized by environmentalists for supporting off-shore oil and gas explorations, a large decline in its environmental budget, and proposals for two new coal-fired electricity power plants (Harrison 2012). Those in the business community with close ties to the Liberal government were taken by surprise. Jock Finlayson, the Executive Vice President of the BC Business Council, said:

> *The throne speech was a huge surprise, not just to my organization but to everybody in the corporate community. There really was not any advance notice, either through public statements or even through back channels. I actually dropped my coffee cup, full of coffee, when I was watching the live broadcast.* (Harrison 2012).

The carbon tax rate initially began at \$10 per tonne of CO_2eq and increased by \$5 annually, reaching \$30 in 2012.[14] The \$10 carbon tax represented an increase of 2.4 cents per liter for gasoline and a \$20.8 increase per ton for coal. These numbers rose to 7.2 cents per liter for gasoline (equivalent to 4.4% of the final price) and \$62.4 per tonne of coal (equivalent to 55% of the final price) at the tax rate of \$30 per tonne of CO_2eq. The tax covers all fossil fuels purchased within BC, covering 77% of total provincial emissions (Murray and Rivers 2015).[15] The policy is comprehensive and includes all plants in BC.[16]

The tax is designed to be revenue-neutral. The revenue is returned to consumers and businesses through a direct transfer to low-income individuals (a one time \$100 Climate Action Dividend per adult in the initial year), a decline in income taxes (around 2%

[14] The rate was kept at \$30 until 2018, when increased to \$35 on April 1. It continues to increase by \$5 annually and will reach \$50 in 2022 (Ministry of Finance 2017). An annual increase of \$5 was postponed in 2020 due to the COVID-19.

[15] The uncovered emissions are associated with emissions produced by landfill facilities, non-combustion emissions from the agriculture sector, most fugitive emissions, and industrial emissions that do not come from burning fossil fuels.

[16] There are no manufacturing industries that are exempted from the carbon tax. The agriculture sector was exempted from the tax after 2012, which is not included in our analysis because the focus of this paper is on manufacturing plants.

reduction in 2008 and 5% reduction in 2009 for those who have an annual income of less than \$70,000), a decline in general corporate income taxes (from 12 to 10 percent), and a reduction in small corporate income taxes (from 4.5 to 2.5 percent in the first three years after the implementation of the policy). According to the budget and fiscal plan for 2013, the carbon tax raised about \$1.2 billion in revenues for 2012–2013 and returned about \$1.4 billion to consumers.

3 Theoretical Framework

In this section, we briefly explain how a revenue-neutral carbon tax affects manufacturing emissions and motivate our empirical strategy discussed in Sect. 4. We adapt a simple model of Yamazaki (2022), who theoretically shows that carbon taxes can positively affect manufacturing productivity through recycling the tax revenues to lower the CIT rates. It allows plants to invest in energy-saving technologies and explicitly models the plant-level responses from both the carbon tax and the revenue recycling through the CIT reduction. We extend the model of Yamazaki (2022) to show how the policy affects plant-level emission through output and emission intensity responses.

To begin, let $Z \equiv ex$ denote manufacturing plant's emission, where e and x are its emission intensity and output, respectively. Taking logs and totally differentiating this emission equation yields:

$$\dot{Z} = \dot{e} + \dot{x} \tag{3.1}$$

where $\dot{Z} = dZ/Z$, and so on (i.e., "$\dot{}$" denotes a percentage change). This shows that emission responses to any shocks, including a carbon tax, can be decomposed into two channels. The first term is referred to as the technique effect, while the second term is referred to as the scale effect.[17] We explicitly show further how these two effects are affected by a revenue-neutral carbon tax.

Consider a partial equilibrium model with an iso-elastic demand for manufacturing goods:

$$x = p^{-\sigma}B \tag{3.2}$$

where B is a constant representing aggregate quantity and price indexes, p is the price for the manufacturing goods, and $\sigma > 1$ is elasticity of substitution between differentiated goods.

Following Copeland and Taylor (1994), there is a joint production technology for manufacturing plants:

$$x = A(1-\theta)F(K,L) \tag{3.3}$$

$$Z = \varphi(\theta, I_A)F(K,L) \tag{3.4}$$

where capital (K) and labor (L) are used to produce the potential output, $F(K, L)$. We can think of x to be the net output because some are allocated to abatement. $\varphi(\theta, I_A)$ is

[17] This type of decomposition exercise has been used extensively in the literature, e.g., Antweiler et al. (2001), Cherniwchan et al. (2017), and Najjar and Cherniwchan (2021).

an abatement function, satisfying $\varphi(0, I_A) = 1, \varphi(1, I_A) = 0$, and $\partial\varphi/\partial\theta < 0$. $\theta \in [0, 1]$ is a fraction of inputs allocated to abatement. This means that the level of emission decreases with abatement, but at the cost of output.

Now following Forslid et al. (2018), the abatement function is expressed as follows:

$$\varphi(\theta, I_A) = \frac{(1-\theta)^{1/\alpha}}{\Omega(I_A)} \tag{3.5}$$

with $0 < \alpha < 1$, and $\Omega(I_A)$ is the abatement augmenting technology, which is a function of abatement investment, I_A. It satisfies $d\Omega(I_A)/dI_A > 0$ and is the reciprocal of the amount of emission produced per output. This is a technological parameter for the abatement activity. Equation (3.5) reflects that plants can reduce their emissions by increasing θ or increasing the abatement investment. Using Eqs.(3.3), (3.4) and (3.5), output can be expressed as,

$$x = A\left(\Omega(I_A)Z\right)^{\alpha} F(K, L)^{1-\alpha} \tag{3.6}$$

With this formulation, one can think of Z as an input and re-interpret it as energy.[18] First, we show an expression for e by solving plant's cost minimization problems.

Cost Minimization

From Eq. (3.6), we can see that a plant chooses how much capital and labor for the production of the potential output, F, while choosing the cost-minimized combination of the potential output and energy. By solving the former cost minimization problem with $F(k, l) = k^{\beta} l^{1-\beta}$, the minimum cost of producing a unit of F can be expressed as:

$$c^F(\tilde{r}, \tilde{w}) = \kappa_\beta \tilde{r}^{\beta} \tilde{w}^{1-\beta} \tag{3.7}$$

where $\kappa_\beta \equiv \beta^{-\beta}(1-\beta)^{\beta-1}$, $\tilde{r} \equiv (1 - \lambda_k t^c)r$, and $\tilde{w} \equiv (1 - t^c)w$. r and w are the prices of capital and labor, respectively. t^c is the CIT rate. The cost of labor is fully deductible for tax purposes while only a portion $\lambda_k \geq 0$ of the capital cost is deductible.[19].

λ_k is a highly stylized representation of many CIT systems, intending to reflect the distortionary features of the CIT with regard to capital. The typical case would be $\lambda_k < 1$ because the real cost of capital is not fully deductible. This is because only the nominal cost of debt finance is fully deductible while that of equity finance is not, or because tax depreciation is different from economic depreciation. This incomplete deductibility of capital costs is a source of distortions from the CIT. It increases the before-tax rate of return on the marginal investment required to generate the after-tax hurdle rate of return.[20] This tax wedge between the before- and after-tax rate of return on the marginal investment is

[18] We assume that there is a one-to-one mapping between energy and emission. Yamazaki (2022) argues that a concept of abatement in Copeland and Taylor (1994) is still relevant here, although the regulation they consider is either emission tax or emission standard. Once we interpret Z as energy and θ as a fraction of inputs allocated to energy-saving activities, such as R&D expenditure allocated to energy-saving technology, the formulation of Copeland and Taylor (1994) is still valid. Tombe and Winter (2015) also argue that "one might loosely interpret abatement as any costly activity that lowers the use of emissions-relevant energy, such as substitution between different fuel types." For this reason, investment in energy-saving technology, fuel switching, and factor substitution can all be interpreted as abatement in the definition of Copeland and Taylor (1994).

[19] The incomplete deductibility of capital costs is a common way to represent more complex CIT systems. See Haufler and Schjelderup (2000), McKenzie and Ferede (2017), and Fuest et al. (2018) as examples.

[20] A hurdle rate is the minimum rate of return acceptable by investors.

known as the marginal effective tax rate (METR) on capital,[21] which we discuss further below. When $\lambda_k = 1$, the full opportunity cost of capital is deducted, and the CIT is a tax on economic profit (i.e., the CIT is not distortionary).[22]

Next, by solving the latter cost minimization problem, the minimum cost of producing a unit of x can be expressed as:

$$c^x(\tilde{\tau}, c^F) = \kappa_\alpha A^{-1}\Omega(I_A)^{-\alpha} {c^F}^{1-\alpha} \tilde{\tau}^\alpha \tag{3.8}$$

where $\kappa_\alpha \equiv \alpha^{-\alpha}(1-\alpha)^{\alpha-1}$. $\tilde{\tau} \equiv (1-t^c)\tau$. τ is the carbon tax inclusive energy price. The cost of energy is fully deductible for tax purpose.[23] From Shephard's lemma, the conditional input demand for energy is expressed as:

$$z = \frac{1}{A\Omega(I_A)^\alpha}\left(\frac{\alpha}{1-\alpha}\frac{c^F}{\tilde{\tau}}\right)^{1-\alpha} \tag{3.9}$$

By using the definition of energy intensity, Eq. (3.9) is the expression for energy intensity as Eq. (3.8) is a unit cost function, i.e., $z = e$. What's left to show is the expression for the abatement technology, which plays an important role in shaping the technique effect through investment. The optimal abatement investment is derived from the plant's profit maximization.

Profit Maximization

The plant sets the pricing rule given the abatement investment and then chooses how much to invest in abatement given the pricing rule. Maximizing profits by a monopolistic competitive manufacturing plant yields a pricing rule:

$$p = \frac{\sigma}{\sigma-1}\frac{c^x}{1-t^c} \tag{3.10}$$

Using Eqs. (3.2) and (3.10), plant's profit can be expressed as:

$$\pi = B(\sigma-1)^{\sigma-1}\sigma^{-\sigma}(1-t^c)^\sigma {c^x}^{1-\sigma} - (1-t^c)I_A \tag{3.11}$$

Similar to labor cost, the abatement investment cost is fully deductible.[24] Following Forslid et al. (2018), we assume that $\Omega(I_A) = I_A^\rho$ with $\rho > 0$. Plugging Eq. (3.8) into (3.11), and then maximizing plant's profit with respect to abatement investment I_A yields:

$$I_A = A^{\frac{\sigma-1}{\gamma}}\left((1-\gamma)\Gamma\right)^{\frac{1}{\gamma}}\tau^{-\frac{\alpha(\sigma-1)}{\gamma}}\left(\frac{1-\lambda_k t^c}{1-t^c}\right)^{-\frac{\beta(1-\alpha)(\sigma-1)}{\gamma}} \tag{3.12}$$

21 The concept of the METR has been widely used since the work of King and Fullerton (1984).

22 In principle, $\lambda_k > 1$ is also possible when the tax system subsidizes capital due to accelerated depreciation, investment allowances, and investment tax credits. However, a back-of-the-envelope calculation using the model parameters from the literature shows that λ_k is around 0.77 for British Columbia and is likely to be always less than 1. Thus, we assume $\lambda_k < 1$ for this paper. λ_k can be calculated with information on the METR.

23 In Canada, fuel costs are fully deductible as business expenses. See https://www.canada.ca/en/revenue-agency/services/tax/businesses/topics/sole-proprietorships-partnerships/business-expenses.html.

24 Although Yamazaki (2022) also allows the abatement investment cost to be not fully deductible like capital cost, we abstract away from that for the illustrative purposes.

where $\Gamma \equiv B\sigma^{-\sigma}(\sigma-1)^{\sigma}\left(\kappa_{\beta} r^{\beta} w^{1-\beta}\right)^{(1-\alpha)(1-\sigma)}$ and $\gamma \equiv 1-\alpha\rho(\sigma-1) > 0$.[25] Notice again that when the costs of capital investments are fully deductible, i.e., $\lambda_k = 1$, Eq. (3.12) becomes independent of the CIT. This is simply because there is no distortion in the capital investment market when the CIT is levied on pure profit. In this simple model, one can redefine $(1-\lambda_k t^c)/(1-t^c)$ to be $(1+t^{\mathrm{METR}})$, where t^{METR} is the METR on capital. When $\lambda_k < 1$, t^{METR} is an increasing function of t^c.

Equation (3.12) shows that the abatement investment is a decreasing function of the carbon tax. While this may not be intuitive, Forslid et al. (2018) point out that the abatement investment intensity is an increasing function of the carbon tax.[26] This positive effect is an encouraging policy response towards the emission reduction. On the other hand, the abatement investment is a decreasing function of the CIT,[27] and thus a decreasing function of the METR. This implies that the reduction of the CIT rate has a positive effect on abatement investment through the reduction of the METR.[28] Lowering the before-tax rate of return required on the marginal investment allows more capital projects that were not feasible before, such as energy-saving technologies. Thus, the overall effect of the policy on the abatement investment is ambiguous as the carbon tax and CIT reduction work against each other.

Putting all together yields:

$$e = \frac{1}{A}\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} I_A^{-\alpha\rho} \underbrace{\left(\frac{\left(\kappa_{\beta} r^{\beta} w^{1-\beta}\right)\left(1+t^{\mathrm{METR}}\right)^{\beta}}{\tau}\right)^{1-\alpha}}_{p^r \equiv \text{After-tax relative price between F and z}} \tag{3.13}$$

This shows that both the carbon tax and CIT affect emission intensity through two channels, the after-tax relative price between the potential output (F) and energy (z), and the abatement investment. First, the carbon tax directly affects the emission intensity negatively by decreasing the relative price between the potential output and emission. As expected, it increases the cost of emissions, inducing plants to reduce the level of emissions per unit of output. On the other hand, as explained above, although the effect of the carbon tax on the abatement investment is ambiguous, it could be positive through the market competition.

Second, as p^r is an increasing function of the CIT, a fall in the CIT makes p^r smaller, making the potential output cheaper through the reduction of the METR. This induces a substitution away from z to F to produce a unit of x. As a result, more resources are allocated for the abatement to maintain the same level of the net output with more F and less z. Thus, this reduces emission intensity. At the same time, the reduction of the CIT rate increases abatement investment through the reduction of the METR, resulting in a fall in emission intensity.

From these channels, the implementation of the carbon tax with the reduction of the CIT could reduce emissions through the technique effect.

[25] In order to satisfy the second order condition of the profit maximization problem, γ has to be positive. See Appendix of Yamazaki (2022) for the verification.

[26] This can be easily verified by using Eqs.(3.12) and (3.16).

[27] See Yamazaki (2022) for the verification.

[28] In addition, lowering the METR increases investments in general. Lowering the user costs of capital encourages plants to invest more. This may also make plants more productive through a more traditional manner, i.e., an increase in A.

Next, we demonstrate how the policy affects the scale effect. Plugging Eq. (3.10) into (3.2) yields:

$$x = \psi I_A^{\alpha\rho\sigma}(1 + t^{\mathrm{METR}})^{-\sigma\beta(1-\alpha)}\tau^{-\alpha\sigma}B \tag{3.14}$$

where $\psi = \left(\sigma(1-\sigma)^{-1}\kappa_\alpha A^{-1}\left(\kappa_\beta r^\beta w^{1-\beta}\right)^{(1-\alpha)}\right)^{-\sigma}$. This shows that a carbon tax negatively affects the scale effect by increasing the cost of production while it allows plants to produce more through the increase of the abatement investment. Thus, depending on the size of these two effects, the effect of the carbon tax on the output could go either way. On the other hand, the reduction of the CIT positively affects the scale effect from both channels, directly through the METR and abatement investment.[29]

To summarize, Eqs. (3.13) and (3.14) show that implementing a carbon tax alone would reduce emission at the cost of output. Yet, the negative scale effect can be mitigated by the abatement investment. On the other hand, when the carbon tax revenues are used to lower the rate of the CIT, there is a possibility that plants can lower their emissions while producing more. This is possible because the reduction of the CIT ameliorates the distortion in the capital market and encourages the abatement investment. We demonstrate a simple case in Fig. 1. To simplify the notations, we define $\tilde{Z}$ as $\Omega(I_A)Z$, which is the abatement-technology augmented emission, presented in Eq. (3.6). Panel (a) depicts the most obvious initial response to the policy, i.e., scaling down the production to avoid the tax burden, resulting in a fall in energy consumption and thus emission. On the other hand, panel (b) depicts how plants can produce more with less energy by investments in response to the CIT reduction, i.e., Z is reduced, but $\tilde{Z}$ is increased due to the increase in I_A. Although Fig. 1 is an oversimplified version of what our theory predicts, it provides a clear motivation for an empirical investigation on how all these effects pan out.

Finally, we take a step further to connect our theory to empirical design. Plugging Eq. (3.12) into (3.13) and (3.14) yields:

$$e = \phi_e \Gamma^{-\frac{\alpha\rho}{\gamma}}(1 + t^{\mathrm{METR}})^{\frac{\beta(1-\alpha)}{\gamma}}\tau^{\frac{\alpha-\gamma}{\gamma}} \tag{3.15}$$

$$x = \phi_x \Gamma^{\frac{\alpha\rho\sigma}{\gamma}}(1 + t^{\mathrm{METR}})^{-\frac{\sigma\beta(1-\alpha)}{\gamma}}\tau^{-\frac{\alpha\sigma}{\gamma}} \tag{3.16}$$

where $\phi_e = A^{\frac{\alpha\rho-1}{\gamma}}\left(\frac{\alpha}{1-\alpha}\kappa_\beta r^\beta w^{1-\beta}\right)^{(1-\alpha)}(1-\gamma)^{-\frac{\alpha\rho}{\gamma}}$ and $\phi_x = A^{\frac{\sigma}{\gamma}}\left(\frac{\sigma}{1-\sigma}\kappa_\alpha\left(\kappa_\beta r^\beta w^{1-\beta}\right)^{(1-\alpha)}\right)^{-\sigma}(1-\gamma)^{\frac{\alpha\rho\sigma}{\gamma}}$. Then by plugging Eqs. (3.15) and (3.16) into the emission equation, we have:

$$Z = \phi_e \phi_x \Gamma^{\frac{\alpha\rho(1-\sigma)}{\gamma}}(1 + t^{\mathrm{METR}})^{\frac{\beta(1-\alpha)(1-\sigma)}{\gamma}}\tau^{\frac{\alpha}{\gamma}(1-\sigma)-1} \tag{3.17}$$

Now totally differentiating Eq. (3.17) with respect to the carbon tax (τ) yields:

[29] As before, the reduction in the CIT also leads to higher investment in other capitals, leading to higher output.

$$\frac{dZ}{d\tau} = \underbrace{\left(\frac{\alpha(1-\sigma)}{\gamma} - 1\right)\frac{ex}{\tau}}_{(-)} + \underbrace{\left(\frac{\beta(1-\alpha)(1-\sigma)}{\gamma}\right)\frac{ex}{1+t^{\mathrm{METR}}}}_{(-)}\underbrace{\frac{d(1+t^{\mathrm{METR}})}{d\tau}}_{(-)}$$
$$= \left[\frac{(1-\sigma)[\alpha(1-\rho) + \varepsilon\beta(1-\alpha)] - 1}{\gamma}\right]\frac{ex}{\tau} \tag{3.18}$$

where $\varepsilon \equiv \frac{d(1+t^{\mathrm{METR}})}{d\tau}\frac{\tau}{(1+t^{\mathrm{METR}})} \in (0,-1)$ is the elasticity of the METR with respect to the carbon tax. As the carbon tax rate increases, the reduction of the CIT rate increases due to the revenue-neutrality of the policy. Equation (3.18) shows that the effect of the carbon tax on plant's emissions is a monotonic function of plant's emission intensity.[30] This means that the emission responses would be larger for emission-intensive plants. The sign of the function is ambiguous because the emission effects from the carbon tax and revenue recycling through the reduction of the CIT rate work against each other. This theoretical prediction motivates our empirical strategy, i.e., exploiting the plant-level variation in emission intensity to identify the emission effect. Our simple theory presented in this section, not only connects the theory to the empirics, but also helps us explain our findings better.

4 Empirical Analysis

This section discusses the econometric design to estimate the emission effect of the BC carbon tax. The simple model illustrates that the size of the policy exposure depends on plants' emission intensity. We take advantage of the confidential dataset to directly observe the plant-level emission intensity to measure the policy exposure, which is discussed in detail below.

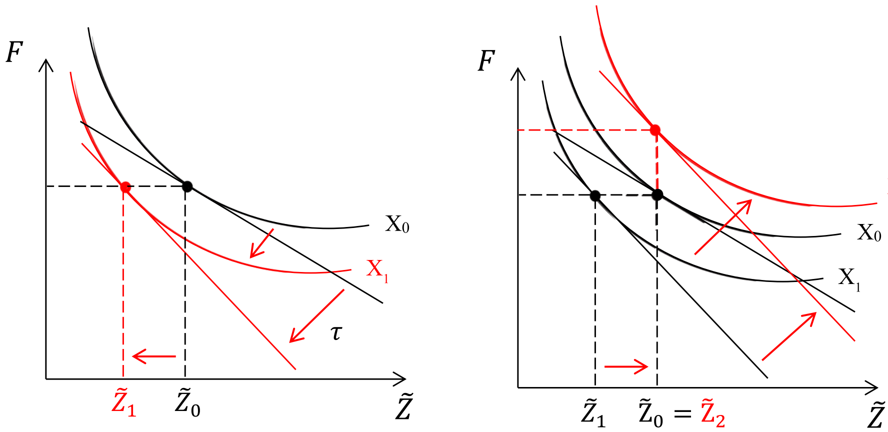
4.1 Methodology

As motivated by Eq. (3.18), we employ a difference-in-differences estimation with differential treatment intensity and estimate the following equation:

$$\ln E_{lipt} = \beta(K_p \times D_t \times EI_l) + \alpha_l + \lambda_{l't} + \phi_{i't} + \delta_{pt} + \epsilon_{lipt} \tag{4.1}$$

where $\ln E_{lipt}$ is the log of GHG emissions from plant l of industry i (at 6-digit NAICS level) in province p at year t. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. EI_l is the average pre-policy emission intensity for plant l. We fix EI_l at the pre-policy level because the emission intensity after 2008 would be an outcome variable and would change due to the carbon tax. α_l is the plant fixed effects that capture plant specific time-invariant characteristics, as well as industry and province time-invariant characteristics that affect GHG emissions. $\lambda_{l't}$ is the high emission-intensive plant by time fixed effects. We denote l' as a group of plants whose EI_l is greater

[30] We also totally differentiate Eqs. (3.15) and (3.16) with respect to the carbon tax, discussed in Appendix A. By doing so, we show that the size of the technique and scale effects also depend on plant's emission intensity. These confirm that the effects of this revenue-neutral carbon tax on plants' emissions through the technique and scale effects are ambiguous due to these countervailing forces.



(a) Scale Effect Alone **(b)** Effect of Abatement Investment

Fig. 1 These figures plot the plant responses to a carbon tax. $\tilde{Z}$ is defined as $\Omega(I_A)Z$, which is the abatement-technology augmented emission. This allows us to model plants choosing to invest in energy-saving technologies so that they can lower the policy burden, i.e., allowing for plants to produce more with less energy. Panel (**a**) depicts the most obvious response to the policy, i.e., scaling down the production to avoid the tax burden, resulting in a fall in energy consumption and emission. Panel (**b**) depicts how plants can produce more with less energy by investments, i.e., Z is reduced, but $\tilde{Z}$ is increased due to the increase in I_A

than a threshold. We use the 70*th* percentile of emission intensity in the whole sample as the threshold.[31] These fixed effects capture any high emission-intensive plant-specific time shocks. $\phi_{i't}$ is sector (at 2-digit NAICS level) by year fixed effects that capture any sector-specific time shocks. δ_{pt} are province by year fixed effects that capture any province-specific and nationwide time shocks. ϵ_{lipt} is the idiosyncratic error term. The interaction term allows us to isolate the emission effect of the BC carbon tax by exploiting three sources of variation.

The first two sources of variation are intuitive. As the policy was implemented in 2008, it created provincial and temporal variations. We can simply compare plants in BC with plants in other provinces before and after the implementation of the policy. The third source of variation originates from the difference in emission intensity across plants. The simple model illustrates that the emission response depends on plants' emission intensity. Intuitively, we claim that high emission-intensive plants have a much larger incentive to reduce their emissions in response to the policy because they would bear a higher cost per output, shown in Table 1. On the other hand, the tax burden for low emission-intensive plants is almost negligible, providing little incentive for them to respond to the policy.[32] This allows

[31] We also explored the different threshold levels, such as 50th, 60th, and 80th percentile. Results are robust to using these different thresholds, shown in Table 10 in Appendix B.2.

[32] Low emission-intensive plants may still have an incentive to reduce their emissions if they pay a considerable amount of tax (i.e., their energy expenditure is large if their output level is high enough). Especially if fuel switching requires only a fixed cost (e.g., a fixed cost to buy new machinery that works with electricity rather than coal and natural gas), then plants' incentives to invest depends only on the absolute value rather than the per unit cost of the carbon tax. Table 1, however, shows that low emission-intensive plants pay much less carbon tax in absolute terms relative to high emission-intensive plants. We also show that high emission-intensive plants produce, on average, higher levels of output in Table 15 of Appendix C.

us to treat low emission-intensive plants as less-affected or control group.[33]Yamazaki (2017) also exploits the variation in the industry emission intensity at the national-level. As our data allows us to directly observe the plant-level emission intensity, we can compare plants based on the intensity of their policy exposure more accurately.

These three sources of variations allow us to employ an augmented DID estimation method. It compares the emission differences between high emission-intensive plants and low emission-intensive plants in BC relative to the same emission differences in the rest of Canada before and after the implementation of the policy.[34] There are several threats to the identification that are worth mentioning here. First, the carbon tax in BC may alter the output level in other provinces through the inter-provincial trades of intermediate goods. Through a cost pass-through, it would make it more expensive for plants in other provinces to produce with the imported intermediate goods from BC. The magnitude of this change depends on the bilateral trade cost. The control group being (indirectly) affected by the policy violates the stable unit treatment value assumption (SUTVA). To test the severity of this concern, we performed a robustness test by using only provinces that have very low trade flows with BC. The baseline estimation results presented in the later section are robust to this sample difference.[35]

Second, one of the unfortunate challenges in identifying the effect of the BC carbon tax is that the timing of the implementation coincides with the Great Recession. Although the negative impacts of the Great Recession may be different across provinces due to the substantial differences in the composition of their economies, it is unlikely that it also had the differential impacts across plants based on their emission intensity, high vs. low emission intensive plants. Being able to exploit the variations at the granular level allows us to mitigate this concern, especially with the fixed effects.

Third, even though the policy announcement was unexpected, it is possible for plants to respond to the policy prior to the actual implementation. Although this may not be as much a concern as the first two threats above, it is worth exploring. In addition, it is also important that we do not capture the differences in pre-existing trends. We examine the anticipatory responses and pre-existing trends using the flexible estimation method, presented in Sect. 5.2.

Fourth, there was a significant change in the price of natural gas in BC in 2009 and 2014. As the sample period for this study is from 2004 to 2012, the price change in 2014 is not a concern, but the price change in 2009 may be. In the augmented DID design, we control for sector specific shocks at the 2-digit NAICS code. Therefore, if the impact of the change in natural gas price is not different between the high emission-intensive and low emission-intensive plants, our estimation method can isolate the impact of the policy from the effect of change in the natural gas price.

β is the coefficient of interest. It estimates the average effect of the BC carbon tax on GHG emissions from treated plants during the 2008–2012 period. The identifying

[33] For an average plant below the 70th percentile in emission intensity, the carbon tax imposes a charge less than 0.05 percent of the plant's total costs.

[34] To ensure the credibility of our estimates, we also estimate Eq. (4.1) with weights based on the estimated propensity scores. This would ensure the similarity between treated and control plants. The propensity scores are estimated using many plant-characteristics, such as output, labor, energy, industry, etc. The results are presented in Table 13 in Appendix B.

[35] The results of this robustness check are presented in Table 11 in Appendix B.

Table 1 The Tax Burden of the BC Carbon Tax for Various Industries

Subsector (NAICS)	Emission intensity (t/$1K)	Tax paid as % of output	Tax paid ($1K)
Panel A. Canada			
5 most emission intensive			
Non-metallic mineral product (327)	0.529	1.06	64,065
Chemical (325)	0.205	0.41	87,897
Paper (322)	0.200	0.40	73,380
Primary metal (331)	0.182	0.36	93,134
Petroleum and coal product (324)	0.092	0.18	38,966
5 least emission intensive			
Miscellaneous (339)	0.020	0.04	1,020
Leather and allied product (316)	0.019	0.04	61
Clothing (315)	0.019	0.04	349
Transportation equipment (336)	0.011	0.02	13,990
Computer and electronic product (334)	0.007	0.01	828
Average	0.087	0.17	23,095
Panel B. British Columbia			
5 most emission intensive			
Non-metallic mineral product (327)	0.827	1.65	10,801
Paper (322)	0.300	0.60	20,115
Primary metal (331)	0.236	0.47	7,901
Textile mills (313)	0.153	0.31	13
Chemical (325)	0.149	0.30	1,446
5 least emission intensive			
Electrical equipment (335)	0.027	0.05	41
Miscellaneous (339)	0.023	0.05	128
Textile product mills (314)	0.023	0.05	48
Clothing (315)	0.012	0.02	19
Computer and electronic product (334)	0.008	0.02	86
Average	0.140	0.28	2,697

This shows the top and bottom five subsectors (3 digit NAICS) in terms of their emission intensities and the average among all subsectors in the dataset. We multiply the average tax rate during the 2008-2012 period (i.e., $20/t$CO_2$e) by subsectors' pre-policy average emission intensity to calculate the average cost imposed on subsectors, reported in column 2. The last column reports the average tax paid for the corresponding subsectors (i.e., multiplying the average tax rate by subsectors' pre-policy average emission)

assumption requires that there are no high emission-intensive plant by province specific shocks to GHG emissions that are contemporaneous to the adoption of the BC carbon tax. In other words, there should not be any other factors aside from the carbon tax that changes the GHG emissions of (more) treated plants differently than those of untreated (or less treated) plants. This assumption fails if, for instance, there is an economic shock that affects high emission-intensive and low emission-intensive plants differently across provinces. We exclude Alberta and Québec as control provinces because they implemented similar policies in 2007.

4.2 Data

To identify the causal effect of the BC carbon tax on GHG emissions, we construct plant-level emission data. To do so, we use a confidential plant-level data set, the Annual Survey of Manufacturing (ASM), which includes (but not limited to) plant-level fuel purchases, shipment destinations, sales, final products, plant location, and plant total production costs. The ASM dataset allows us to calculate plant-level emissions and emission intensity, which cannot be done with other publicly available datasets. To construct our measure of GHG emissions, we collect fuel prices for various cities in all provinces over time, and then divide fuel purchases by fuel prices to determine the fuel quantities for each plant.[36] Finally, using the embodied GHG emission of each fuel type,[37] we calculate GHG emissions at the plant-level and divide by the plant's output value to find the emission intensity. This is the most comprehensive plant-level dataset for GHG emissions in Canada. These steps are shown in a simple flowchart in Fig. 2.

Quick (2014) shows that calculating emissions by fuel consumption is a more accurate way to determine GHG emissions when compared to using observed emissions from emissions monitoring systems. Linn et al. (2015) show that these two alternative measures of emissions are very consistent with each other, and the results are not statistically different. In sum, previous research suggests that the lack of emissions data in the ASM dataset is not of concern with regards to our analysis. Our method of calculating GHG emissions should be more accurate than using self-reported emissions or at least consistent with it.

Table 2 presents summary statistics of key variables in the data.[38] To motivate our empirical strategy further, in Panel A, we report the means of key variables for four categories: (1) high emission-intensive plants in BC (BC-High), (2) low emission-intensive plants in BC (BC-Low), (3) high emission-intensive plants in ROC (ROC-High), and (4) low emission-intensive plants in ROC (ROC-Low). These show that the means of these key variables for High and Low are reasonably similar between BC and ROC, which is important for the identification. Panel B shows the means of emission in log for the same categories as Panel A. Furthermore, we break the data into the pre- and post-policy periods and report the differences in the means for each period, shown in column 3 for BC and ROC. We perform *t*-test on such differences. In the last two rows of Panel B, we manually calculate the emission effect of the policy by the difference-in-differences and triple differences. These naïve calculations of the emission effect provide suggestive evidence that the policy might have contributed to the emission reduction, and that it is worth moving forward with a more rigorous econometric technique to isolate its emission effect.

[36] Fuel prices for gasoline, diesel, propane, light fuel oil, and heavy fuel oil are retrieved from Natural Resource Canada (2016), prices for natural gas are retrieved from Statistics Canada (2015), and coal prices are retrieved from Natural Resource Canada (2012). The fact that, for each fuel, we use the average price in major cities in each province is a potential source of concern. This average price can be different from the exact price that each plant faces because plants may have different contracts and strategies for buying their fuels. This difference creates a certain degree of error in measuring plant-level GHG emissions. However, if the measurement error does not vary systematically with the treatment (i.e., the error is not larger or smaller for plants that are more exposed to the policy and only after the carbon tax is introduced), it will only increase the noise in the data, inflating the standard errors, but it would not undermine our ability to identify the effect of interest.

[37] The embodied GHG emissions by fuel type are available on the Environment Canada website.

[38] To visualize the data better, we also include a few figures (Figs. 6 and 7) that may be useful in Appendix C.

In addition, we present the trends of emission for BC and ROC in Fig. 3. Panel (a) shows the average emission trends for BC and ROC, while Panel (b) shows the trends of differences in average emissions between high and low emission intensive plants for BC and ROC. These figures also corroborate the suggestive evidence from Table 2, i.e., emissions decline in BC relative to ROC. Moreover, these also show that the pre-policy trends are reasonably parallel between BC and ROC, justifying the use of the augmented DID method.

As our data is survey data, there is an issue of missing data, in particular 32 percent of manufacturing plants in the data do not report their energy expenditure by fuel types.[39] These plants are excluded from the analysis. There are three reasons why some plants do not report their energy expenditures: (1) plants were not active in the relevant years; (2) plants did not fill the fuel expenditure section of the survey; (3) those plants are administrative plants and not manufacturing plants, and so they do not use any fuels. There is no correlation between the size of plants and missing data for energy expenditure. Therefore, if plants that did not report their energy expenditure were not active for a reason other than the carbon tax, or are not systematically different from other plants, there will be no selection problem that undermines the identification strategy. Moreover, the sample is restricted to include plants that appear in the dataset at least once before and once after the implementation of the BC carbon tax.

Another concern is that the ASM dataset does not include electricity generation plants. The electricity generation in BC is primarily from hydro, which emits negligible emissions, and thus would not be of concern in our analysis. Furthermore, plants are taxed only for their direct purchases of fossil fuels; therefore, we focus only on direct GHG emissions from manufacturing plants and abstract from indirect emissions from electricity consumption.

5 Results

The results are presented in the following subsections. Section 5.1 presents the estimates of Eq. (4.1), while Sect. 5.2 shows the results from robustness checks. Section 5.3 explores the heterogeneous responses to the policy. Section 5.4 estimates the scale and technique effects of the policy to discuss the emission reduction mechanisms through the decomposition exercise.

5.1 Main Results

The results of four specifications based on Eq. (4.1) are reported in Table 3. As we are using the constructed emission data based on fuel expenditures from a survey-based dataset, there is a concern of measurement error in both the outcome (i.e., plant-level GHG emissions) and treatment variable (i.e., emission intensity of plants).[40] Following

[39] We provide summary statistics for those plants that are excluded from the analysis in Table 16 in Appendix C.

[40] Measurement error in the dependent variable is less of concern because it only reduces precision in estimating the standard error, but the coefficient would be unbiased. The measurement error in emission intensity is more of concern because it causes attenuation bias, as it biases the estimates downward. For more details regarding measurement errors in panel data, see Griliches and Hausman (1986). We use plants'

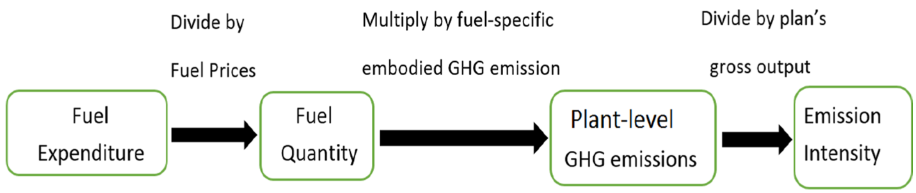


Fig. 2 Steps for calculating emission intensity

Table 2 Summary statistics

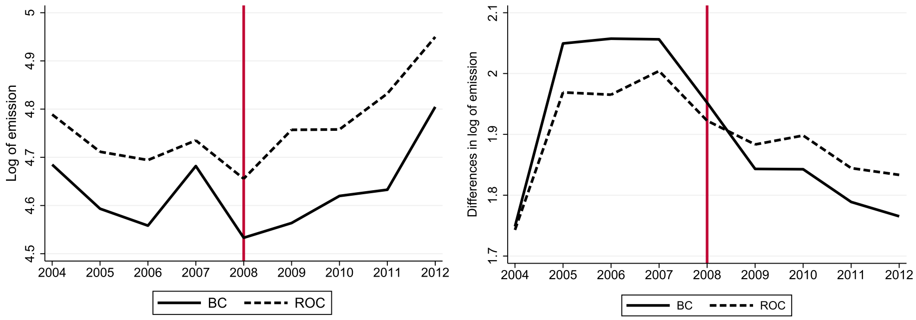
Panel A. Key variables	BC			ROC		
	High	Low	All	High	Low	All
Emission (tons)	4,362	179	1,772	5,460	337	1,818
Energy expenditure ($1K)	1,203	112	526	1,713	252	675
Output ($1K)	21,051	7,752	12,816	27,502	19,287	21,661
Salary workers	10	9	9	17	14	15
Production workers	43	26	33	53	42	45
Age	8.57	8.57	8.57	8.56	8.54	8.54
Total expenses ($1K)	23,769	8,327	14,207	33,805	20,777	24,543
Panel B. Emission (log)	BC			ROC		
	Low	High	Diff	Low	High	Diff
Pre-policy (2004-2007)	3.87	5.85	1.98***	4.18	6.10	1.92***
	(1.39)	(1.97)	[0.046]	(1.41)	(1.86)	[0.018]
Post-policy (2008-2012)	3.93	5.77	1.84***	4.25	6.12	1.88***
	(1.50)	(2.03)	[0.043]	(1.55)	(1.92)	[0.017]
Difference-in-differences			-0.139***			-0.044**
			[0.059]			[0.022]
Triple differences						-0.095
						[0.061]

This shows summary statistics for key variables in the dataset. Panel A breaks the data into two ways: (1) BC and ROC, and (2) high emission-intensive and (High) and low emission-intensive plants (Low). It reports the mean of key variables for each category. Panel B shows the means of emissions in log for the same categories as Panel A. In addition, we break the data into the pre- and post-policy periods and report the differences in the means for each period, shown in column 3 for BC and ROC. We perform *t*-test on such differences. Standard deviations are reported in the parenthesis, while standard errors arereported in brackets. In the last two rows of Panel B, we manually calculate the emission effect of the policy by the difference-in-differences and triple differences

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

Chowdhury and Nickell (1985), we address the measurement error by taking the average of both emission and emission intensity variables across plants within the same city, industry (6-digit NAICS code), province, and year, i.e., the outcome variable is now $\ln E_{cipt}$ where

Footnote 40 (continued)
emission intensity prior to 2008, meaning that the measurement error would not be correlated with the treatment variable.



(a) Average emissions **(b)** Differences in average emissions

Fig. 3 This figure plots emission trends for BC and ROC. Panel (**a**) presents the trends of average emission for BC and ROC, while Panel (**b**) presents the trends of differences in average emissions between high and low emission intensive plants for BC and ROC

Table 3 Baseline Estimates for Emissions

	Plant-level				City by industry-level (MEC)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$K_p \times D_t \times EI_l$	−0.20	−0.15	−0.44***	−0.39***				
	(0.16)	(0.16)	(0.08)	(0.07)				
$K_p \times D_t \times EI_{cip}$					−0.26**	−0.23**	−0.37***	−0.34***
					(0.10)	(0.10)	(0.05)	(0.05)
Plant	Y	Y	Y	Y				
City × industry					Y	Y	Y	Y
Sector × time		Y		Y		Y		Y
Controls			Y	Y			Y	Y
MEC					Y	Y	Y	Y
N	117,445	117,445	77,937	77,937	41,548	41,548	27,462	27,462
R^2	0.90	0.91	0.93	0.93	0.93	0.93	0.95	0.95

Dependent variable for columns (1) through (4) is log of plant-level emission, while that for columns (5) through (8) is log of city by industry-level emission. EI_l is the average pre-policy emission intensity for plant l, while EI_{cip} is the average pre-policy emission intensity for city c, industries i, and province p. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Industry refers to the 6-digit NAICS industry while sector refers to the 2-digit NAICS industry. Columns (3), (4) and (7), (8) includes additional controls, i.e.,plant's age, input-output ratio, the number of plants owned by the parental firm, and export volume. MEC stands for measurement error correction. All specifications include high emission intensive plant by time FEs, and province by time FEs. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (at 2-digit NAICS), reported in parentheses

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

c denotes city. With this measurement error correction (MEC), we estimate the following equation:

$$\ln E_{cipt} = \beta(K_p \times D_t \times EI_{cip}) + \alpha_{ci} + \lambda_{\widehat{ci}t} + \phi_{i't} + \delta_{pt} + \epsilon_{cipt} \tag{5.1}$$

where EI_{cip} is the average pre-policy emission intensity for industry i in city c of province p. Instead of the plant fixed effects, we include α_{ci}, which is the city by industry (6-digit NAICS) fixed effects. $\lambda_{\widehat{ci}t}$ is the high emission-intensive city-industry by time fixed effects. We denote $\widehat{ci}$ as a collection of city-industry pair whose EI_{cip} is greater than a threshold (70^{th} percentile of emission intensity).

Chowdhury and Nickell (1985) show that dividing the sample into different groups and taking the average within each group would reduce the measurement error to a large extent. This is especially true when the variable with measurement error is serially correlated. In our case, the emission and emission intensity variables have a high level of serial correlation over time and across plants within the same 6-digit NAICS code. Each industry-city pair contains about 3 plants. We expect that taking the average of both emissions and emission intensity in these two dimensions reduces the measurement error. This approach would reduce the attenuation bias and improve the precision of the standard error estimations. As shown in Eq. (5.1), the downside of this approach is that we cannot control for confounding factors at the plant-level. However, given the size of each city-industry pair, the city by industry fixed effects are still as powerful as the plant fixed effects in controlling for the confounding factors.

We present the results in Table 3.[41] First, four columns report coefficients from estimating Eq. (4.1), whereas the last four columns report coefficients from estimating Eq. (5.1). Plant-level estimates include the plant fixed effects, while the MEC estimates include the city by industry (6-digit NAICS) fixed effects. In all columns, we control for high emission-intensive plant by time fixed effects, and province by time fixed effects. Sector (at 2-digit NAICS) by time fixed effects are included in columns (2), (4), (6), and (8). We also add additional control variables as the robustness checks. We include plant's age, input-output ratio, the number of plants owned by the parental firm, and export volume. Standard errors are clustered at the level of province by sector (2-digit NAICS).[42] The sample spans 2004 to 2012 and includes only plants that appear in the data set at least once before and once after implementation of the carbon tax.

All specifications show negative signs with similar magnitudes, implying that the carbon tax had a negative impact on the manufacturing emission in BC. While the point estimates without the MEC (columns 1 and 2) are not statistically different from zero, adding the additional controls makes the coefficients statistically significant and slightly larger than those without the controls.[43] As expected, the MEC improves the precision of the

[41] In Appendix B.1, we discuss the importance of Eqs. (4.1) and (5.1). We present the estimates from a more conventional DID estimator.

[42] We also cluster the standard errors at the province level as well as province by 3-digit NAICS subsector level, and results are similar. Mackinnon and Webb (2020) show that under-clustering (i.e., clustering at the 3-digit NAICS subsector by province) suffers from a severe over-rejection, implying that ignoring the within-province correlation is worse than having too few cluster groups (i.e., clustering at the province level). Thus, we cluster at the 2-digit NAICS sector by province.

[43] Despite the statistically significant results from columns (3), (4), (7), and (8), these control variables, especially input-output ratio, the number of plants owned by the parental firm, and export volume, may be bad controls as they could also be the outcome variables. Including these may bias the results. In addition, adding these controls drops about 30 percent of the data used in the estimates without the controls. For these reasons, we prefer to treat these estimates as the robustness checks.

estimations so that the coefficients from columns (5) through (8) are all negative and statistically significant. Although adding the sector by time fixed effects reduces the size of the coefficients slightly, the point estimates are robust to the inclusion of such fixed effects.

Using the point estimate from our preferred specification (column 6), the carbon tax reduced the plant-level manufacturing emission, on average, by 4 percent.[44]

5.2 Robustness Checks

As we attempt to estimate the causal effect of the policy on emissions, it is important that we explore the robustness of our main estimates presented in the previous subsection. We conduct a series of robustness checks below and find little evidence that undermines our main results.

5.2.1 Anticipatory Effect

Despite the quick implementation of the policy, plants might have anticipated the policy and changed their behavior prior to the implementation of the policy. The policy was announced unexpectedly, but plants might still get informed prior to the announcement. To test for the presence of an anticipatory response, we use an event-study method to investigate the evolution of the emission effects during the sample period, treating 2006 as the base year.[45] We estimate the following equation:

$$\ln E_{lipt} = \sum_{t \in T'} \beta_t (\gamma_t \times K_p \times EI_l) + \alpha_l + \lambda_{l't} + \phi_{i't} + \delta_{pt} + \epsilon_{lipt} \tag{5.2}$$

where $T' = \{2004, 2005, 2007, 2008, ..., 2012\}$. γ_t is the year dummy. If there is no anticipatory effect, the emission effect for 2007 should be zero. In addition, this event study analysis allows us to test whether the main estimates are not driven by the difference in the pre-policy emission trends between treated and control plants. Similar to the anticipatory effect, the emission effects should be zero for all years during the pre-policy period (2004-2007) if there is no difference in the pre-policy trends, i.e., $\beta_{2004} = \beta_{2005} = \beta_{2007} = 0$.

The results from estimating Eq. (5.2) are shown in Fig. 4. The point estimates for the pre-policy period are all close to zero (i.e., precisely estimated zero), which confirms that there is no anticipatory response to the policy or difference in the pre-policy emission trends between treatment and control groups. It is clear from the figure that the emission effects are declining after the implementation of the policy.

5.2.2 Permutation Test

To explore the robustness of our results further, we perform a permutation test based on placebo carbon taxes (Bertrand et al. 2004). Based on Eq. (4.1), the treatment variable is the interaction of three variables, i.e., province × year × emission intensity, allowing us to

[44] This 4 percent reduction is calculated by $100 \times \left(e^{(\hat{\beta}\ \overline{\Delta EI_l})} - 1\right)$ where $\overline{\Delta EI_l}$ is the difference of the average emission intensity between high emission-intensive and low emission-intensive plants in BC. We also calculated the upper and lower bounds for the emission effect, which are 0.5 and 7.6 percent reduction, respectively.

[45] This method is also referred to as a flexible estimation.

randomly select a set of a different year, province, and policy exposure intensity to construct a "placebo carbon tax." We estimate the emission effect of the placebo carbon tax and then repeat this process 1,000 times to generate a distribution of the placebo effects. As these placebo carbon taxes are randomly constructed, the emission effect, on average, should be zero.

Figure 5 plots a kernel density distribution of the emission effect of the placebo carbon taxes. The mean of the placebo estimates is centered around zero, and moreover, the point estimates from the main results in Table 3 fall in the extreme left tail of the distribution. This suggests that the emission effects identified in the main estimates are not biased by the spillover effects, which validates the SUTVA in this context.

5.2.3 Dynamic Panel Estimates

Another potential issue in our main estimation is that we do not allow for a possibility of persistence in emissions. This means that we need to consider the autocorrelation in the emission equation. We check the robustness of our main results by taking the autocorrelation issue into account in three ways. First, we re-estimate Eq. (4.1) with the heteroskedasticity and autocorrelation consistent (HAC) standard errors. Second, we simply add the lagged dependent variable in Eq. (4.1). Third, we employ Arellano and Bond (1991)'s GMM estimator to address the potential biases in the dynamic panel data model.

Table 4 shows that the main estimates presented in Table 3 are robust to allowing for the persistency of emissions. The estimates are statistically significant and negative, while the magnitudes are also similar. We also test the existence of the autocorrelation, presented in the last two rows of columns (5) and (6). These confirm that including the one-year lagged emission is sufficient in the dynamic panel model as the existence of the 2nd order autocorrelation is rejected at the AR(2) test.

5.3 Heterogeneous Effects

The analyses to this point have focused on the average effects of the carbon tax on plant emission. To take advantage of the rich dataset, we explore the heterogeneous responses to the policy based on different plant characteristics. We do this by grouping plants into three dimensions. First, we allow the emission effect to differ across large, medium, and small plants based on the size of their production. Second, we explore whether the firm structure matters for the emission responses, i.e., singly-owned plants and multi-plant firm's plants. Third, we allow for the differential effects based on their sectoral trade intensity. The results are reported in Table 5.

There are several interesting results worth discussing. First, the medium and small plants respond more than the large plants. In particular, the size of the emission reduction is the largest for the medium plants. This may imply that the policy burden falls more on the medium plants than large or small plants. Second, the singly-owned plants respond to the policy more than the multi-plant firms' plants. These heterogeneous responses are consistent with results found in Yamazaki (2022) that the medium singly-owned plants are the ones responding to the policy the most. Lastly, plants in the high trade-intensive subsectors respond more to the policy than plants in the medium or low trade-intensive subsectors. This is also consistent with the claim that the emission-intensive and trade-exposed industries are the ones that are most susceptible to the policy, losing their competitiveness in

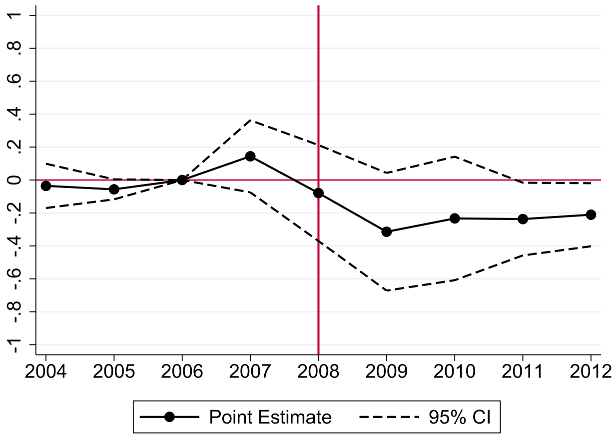


Fig. 4 This figure plots the point estimates from the event-study method estimation, treating 2006 as the base year. The solid red line indicates the year of the policy implementation. The y-axis is the percentage change in emission, while the x-axis is year

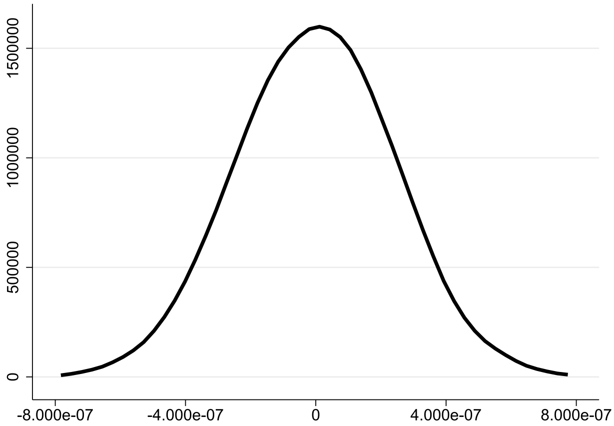


Fig. 5 This figure plots a kernel density distribution of 1000 placebo estimates of the emission effects of the carbon tax. The x-axis is the placebo emission estimates

the global market. For this reason, although their emission reduction may come from the decline in production size, it is also possible that they respond to the policy by improving their energy efficiency to lower their policy burden.

5.4 Decomposition: Scale Versus Technique Effects

As discussed in Sect. 3, emissions can decrease by technological improvement (technique effect), a reduction in output (scale effect), or both. This implies that the 4 percent reduction in emission found in the previous subsection could be solely due to the scale effect, which would mean that the emission reduction would necessarily come at the cost of manufacturing output. To explore the possible mechanisms behind the emission reduction, we directly investigate the scale and technique effects of this policy. We re-estimate Eq. (4.1) with the log of output and the log of emission intensity being the dependent variables. The results are shown in Table 6.

Contrary to the prior concern regarding the scale effect described above, Table 6 shows an interesting and appealing result, i.e., the estimated scale effects are statistically significant and positive. This suggests an increase of the manufacturing output in response to the

Table 4 Addressing the autocorrelation

	HAC		Lagged		GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
$K_p \times D_t \times EI_{cip}$	−0.26***	−0.23***	−0.192***	−0.165***	−0.189***	−0.162**
	(0.07)	(0.07)	(0.057)	(0.06)	(0.06)	(0.06)
$\ln E_{cipt-1}$			0.4***	0.399***	0.421***	0.423***
			(0.01)	(0.014)	(0.034)	(0.033)
Sector × time		Y		Y		Y
N	41,548	41,548	36,397	36,397	31,601	31,601
R^2	–	–	0.95	0.95	–	–
AR(1) test	–	–	–	–	0	0
AR(2) test	–	–	–	–	0.23	0.25

Dependent variable is log of city by industry-level emission. EI_{cip} is the average pre-policy emission intensity for city c, industries i, and province p. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Industry refers to the 6-digit NAICS industry while sector refers to the 2-digit NAICS industry. All specifications employ the measurement error correction and include city by sector FEs, high emission intensive plant by time FEs, and province by time FEs. The coefficients in columns (1) and (2) are the same as columns (5) and (6) of Table 3 but the values in parentheses are the heteroskedasticity and autocorrelation consistent (HAC) standard errors. Columns (3) and (4) add the lagged dependent variable ($\ln E_{cipt-1}$). Columns (5) and (6) estimate the Arellano and Bond dynamic panel model. We also report the p-value from the AR(1) and AR(2) tests

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

Table 5 Effects of the BC carbon tax by different plant characteristics

	Plant size			Firm structure		Trade intensity		
	Large	Medium	Small	Single-plant	Multi-plant	High	Medium	Low
$K_p \times D_t \times EI_l$	−0.18***	−1.54*	−0.59**	−1.14***	−0.14***	−0.47***	−0.15	−0.36
	(0.039)	(0.905)	(0.233)	(0.404)	(0.029)	(0.038)	(0.226)	(0.489)
N	23,053	23,447	23,603	66,838	11,099	34,022	25,057	14,858
# of Plants	3,957	3,968	3,971	11,299	1,944	5,836	5,074	2,569
R^2	0.94			0.94		0.94		

Plant size is determined by output. A plant is large if its output is above the 70th percentile, medium if its output is between the 35th and 65th percentiles, and small if its output is below the 25th percentile. Under Firm structure, we compare plants that are singly owned with plants whose parental firm owns multiple plants. For Trade intensity, we first group subsectors (3-digit NAICS) into three groups based on their trade intensity and create a dummy for each group. Then we interact these subsectoral dummies with our main treatment variables. High trade-intensive subsectors are 327, 323, 337, 321, 332, 324, and 312. Medium trade-intensive subsectors are 311, 339, 326, 322, 325, 331, and 336. Low trade-intensive subsectors are 333, 314, 313, 316, 315, 334, and 335. All specifications include plant FEs, high emission intensive plant by time FEs, sector (2-digit NAICS) by time FEs, province by time FEs, and plant-level control variables. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (at 2-digit NAICS), reported in parentheses

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

Table 6 Estimates for Scale and Technique Effects

	Output		Emission intensity	
	(1)	(2)	(3)	(4)
$K_p \times D_t \times EI_l$	0.059*	0.097***	−0.208	−0.325***
	(0.032)	(0.018)	(0.141)	(0.096)
MEC		Y		Y
N	117,445	41,548	117,445	41,548
R^2	0.95	0.96	0.78	0.82

Dependent variable is log of plant-level output and log of plant-level emission intensity. EI_l is the average emission intensity for plant l from the pre-policy period. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. It includes high emission intensive plant by time FEs, province by time FEs, sector (2-digit NAICS) by time FEs, and city by industry (6-digit NAICS) FEs. The measurement error correction (MEC) is applied to the specification in columns (2) and (4). To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (2-digit NAICS), reported in parentheses

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

policy. The point estimate shows that the plant-level output increases, on average, by 1.8 percent.[46]

If the scale effect is positive, emissions can decline only through the improvement of technology. The estimated technique effects, shown in Table 6, confirm that the policy led to a decline in emission intensity. The point estimate from column (4) suggests that emission intensity decreased, on average, by 6 percent.[47]

Based on our simple model in Sect. 3, there are two possible channels through which this particular policy could generate this positive technique effect (i.e., the reduction in emission intensity). The first is that the carbon tax could directly provide an incentive for plants to invest in energy-saving technologies.[48] This is because plants may wish to lower the long-run financial costs of paying the carbon tax.

The second channel is through the reduction of the CIT rates. As a CIT is essentially a tax on capital, reducing its rate would improve distortion in plants' decision on capital. This may incentivize plants to invest. What is different from the first channel is that this channel could also explain the positive output effect found in this subsection because plants may also invest in productivity-enhancing technologies. As lowering the user costs of capital provides incentives for all types of capital, not just energy-saving related capital, these investments may allow plants to produce more with the same amount of inputs or even

[46] This 1.8 percent increase is calculated using the same method as the emission effect, and its upper and lower bounds are 2.5 and 1.2 percent, respectively.

[47] This 6 percent decline is calculated using the same method as the emission effect, and its upper and lower bounds are 2.5 and 9 percent reduction, respectively.

[48] This can be mathematically seen in Eq. (A.1) in Appendix A, specifically in the first term. Even if the carbon tax revenues were not recycled (i.e., the second term becomes zero without the revenue recycling), the effect of the carbon tax alone on emission intensity is ambiguous.

fewer inputs. This is why it may be possible for plants to reduce emissions while producing more.[49]

One concern here is the measure of output. The ASM does not provide the quantity of output produced, instead it records the total sales (i.e., the product of the price and quantity). The increase in output found in this section can also be due to the increase in price. Although there is no direct way to test or isolate the price effect, we argue that this may not be much of a concern in this particular context because a majority of plants in the sample are heavily traded internationally.[50] This implies that their output prices are determined at the world market, not set by individual plants. This is especially true for Canadian manufacturing plants as Canada is considered as a small open economy. Yamazaki (2022) confirms this view in the context of productivity.

Putting together the results, manufacturing plants seem to respond to a revenue-neutral carbon tax by investing in both energy-saving and productivity-enhancing technologies, allowing them to lower emissions while producing more.

6 Aggregate Implications

In our model, Eq. (3.1) shows that the plant-level emission responses can be decomposed into the scale and technique effects. Using the same decomposition technique, we discuss how these plant-level responses translate into the response in aggregate manufacturing emissions. In this section, we show how we can use the estimates (scale and technique effects) identified in Sect. 5.4) to quantify the effect of the policy on the aggregate emission.[51]

Following Cherniwchan et al. (2017), we suppose that the manufacturing, m, is composed of a continuum of plants, and we can express aggregate manufacturing emission as:

$$Z_m = \int_0^{n_m} z_m(n)dn = \int_0^{n_m} x_m(n)e_m(n)dn \tag{6.1}$$

where $z_m(n)$, $x_m(n)$, and $e_m(n)$ are plant n's emission, output, and emission intensity, respectively. n_i denotes the marginal plant that is endogenously determined by the industry's profitability. Taking logs and differentiating yield:

$$\dot{Z}_m = \int_0^{n_m} \dot{x}_m(n)\eta_m(n)dn + \int_0^{n_m} \dot{e}_m(n)\eta_m(n)dn + n_m\eta_m(n_m)\dot{n}_m \tag{6.2}$$

where $\eta_m(n)dn$ is plant n's share of manufacturing emission. The first term of Eq. (6.2) is the scale effect, while the second term is the technique effect for the aggregate emission. Unlike the plant-level decomposition, there is an additional term, i.e., the third term is

[49] Although we theoretically show that these are the possible explanations, we never formally test these channels in this paper. For this reason, we do not claim that these are the only explanations. To test these possible explanations, we need to separately estimate the emission effect of the carbon tax and CIT reduction.

[50] We indirectly explore this by interacting our main treatment variable with subsector trade intensity. The results are presented in Table 12 in Appendix B. We show that the coefficient shown in Table 3 is fairly close to the coefficient for highly trade-intensive subsectors in Table 12, implying that our assumption on price effect may be justified.

[51] We present the mathematical derivations of the decomposition equation in Appendix B.6.

the selection effect. This effect captures the change in manufacturing emission from plant entries and exits in response to the policy.

We adapt an approach developed by Najjar and Cherniwchan (2021) to derive an empirical analogue to Eq. (6.2). Let t index time, such that manufacturing emission at time t is defined as $Z_{mt} = \int_0^{n_{mt}} x_{mt}(n)e_{mt}(n)dn$, where $x_{mt}(n)$, $e_{mt}(n)$, and n_{mt} are analogous to their counterparts in Eq. (6.2). Then, the change in manufacturing emission between $t-1$ and t can be expressed as[52]

$$\begin{aligned}\Delta Z_{mt} = &\int_0^{n_{mt}} x_{mt}(n)e_{mt}(n)dn - \int_0^{n_{mt}} x_{mt-1}(n)e_{mt-1}(n)dn \\ &+ \int_{n_{mt}\in\, n^{\text{Enter}}} x_{mt}(n)e_{mt}(n)dn - \int_{n_{mt}\in\, n^{\text{Exit}}} x_{mt-1}(n)e_{mt-1}(n)dn\end{aligned}$$

By following the similar algebra in Najjar and Cherniwchan (2021), we can show that the percentage change in manufacturing emission, $\dot{Z}_{mt} = \frac{Z_{mt}-Z_{mt-1}}{Z_{mt-1}}$, is:

$$\begin{aligned}\dot{Z}_{mt} = &\int_0^{n_{mt}} \eta_{mt-1}(n)\dot{s}_{mt}(n)dn + \int_0^{n_{mt}} \eta_{mt-1}(n)\dot{e}_{mt}(n)dn \\ &+ \int_{n_{mt}\in\, n^{\text{Entry}}} \frac{z_{mt}(n)}{Z_{mt-1}}dn - \int_{n_{mt}\in\, n^{\text{Exit}}} \eta_{mt-1}(n)dn \\ &+ \int_0^{n_{mt}} \eta_{mt-1}(n)\dot{s}_{mt}(n)\dot{e}_{mt}(n)dn\end{aligned} \tag{6.3}$$

The first four terms of Eq. (6.3) are the scale, technique, and selection (entry and exit) effects that we discussed above, while the final term is an interaction effect between the scale and technique effects. Najjar and Cherniwchan argue that this can be interpreted as the approximation error in Eq. (6.2) caused by focusing on small, instead of potentially large, changes.

As we already have the estimates for the scale and technique effects from Sect. 5.4, we now need to estimate the selection effect. We explain how we estimate the selection effect and present the result here. We estimate the following equation:

$$N_{jpt} = \beta(K_p \times D_t \times EI_{jp}) + \alpha_{jp} + \lambda_{\widehat{jp}t} + \phi_{j't} + \delta_{pt} + \epsilon_{jpt} \tag{6.4}$$

where N_{jpt} is either the number of entering or exiting manufacturing plants in industry j (4-digit NAICS) in province p at year t. The interaction term, $K_p \times D_t \times EI_{jp}$, is the treatment variable, which is defined as the same as Eq. (4.1) except we use EI_{jp}. EI_{jp} is the average pre-policy emission intensity for industry j in province p. Instead of the plant fixed effects, we include α_{jp}, which is the industry (4-digit NAICS) by province fixed effects. $\lambda_{\widehat{jp}t}$ is the high emission-intensive industry-province by time fixed effects. We denote $\widehat{jp}$ as a collection of industry-province pairs whose EI_{jp} is greater than a threshold (70^{th} percentile of emission intensity). $\phi_{j't}$ is the subsector (3-digit NAICS) by time fixed effects while δ_{pt} is the province by time fixed effects. Finally, ϵ_{jpt} is the idiosyncratic error term at industry by province by time.

The results are reported in Table 7. These suggest that the extensive margin responses to the policy are rather limited. We find no statistically significant exit effect while the

52 While Najjar and Cherniwchan (2021) assume that plant only exit, we allow plants to both enter and exit.

policy increase the number of entrants by 3 plants (column 4). This amounts to 33% of the average entries in BC's manufacturing industries (at 4-digit NAICS).[53] Investigating the selection effect of the policy is important, especially for the policymakers, because the public worries that putting a price on carbon emissions would push some businesses into bankruptcy, exiting the market. Despite this concern, the results presented here suggest otherwise. The increase in the number of entrants in response to the policy may be an appealing finding. Even with the carbon tax in place, manufacturing firms are establishing new plants in BC. Although not tested, this may be because the corporate income taxes are reduced in BC. Some firms may find it profitable to locate their plants in BC despite the carbon tax as the financial benefits coming from the CIT reduction may outweigh the costs from the carbon tax.

Now with all the point estimates for the scale, technique, and selection effects, we can calculate the change in aggregate emissions using Eq. (6.3). We report each component of Eq. (6.3) in Table 8 and add the total effect in column 5. The results show that the aggregate emission is estimated to decline by 4%, which is mainly a result of the scale and technique effects. This decomposition exercise illustrates that the reduction of the aggregate manufacturing emissions comes from the intensive margin adjustments of the surviving plants to the policy.

7 Discussion and Conclusion

This paper takes advantage of a unique confidential plant-level dataset and uses the revenue-neutral carbon tax in BC as an ideal setting to estimate the effect of a carbon tax on GHG emissions from manufacturing plants. We directly observe the plant-level policy exposure through emission intensity, allowing us to employ an augmented DID estimation. This method allows us to isolate the causal effect of the carbon tax on manufacturing emissions.

We find that the BC carbon tax led to a decline in plant-level manufacturing emissions by 4 percent. Furthermore, we explore the mechanisms behind this emission reduction. We find that output increased by 1.8 percent while emission intensity decreased by 6 percent in response to the policy. This suggests that, on average, manufacturing plants respond to the revenue-neutral carbon tax by producing more with less energy. We argue that this may be possible because reducing corporate income taxes encouraged plants to invest in both energy-saving and productivity-enhancing technologies, allowing plants to be more efficient in their production. We also find considerable heterogeneity in emission responses to the policy across plants with different characteristics, such as plant size, ownership types, and trade intensity. For example, singly-owned plants are affected more negatively than multi-plant firms' plants.

Although not formally tested, we hypothesize that the appealing findings of this paper may come from the revenue-neutrality of this policy, especially the reduction of the corporate income tax. Our simple theory shows that emission reduction from the carbon tax alone is likely to come at the cost of output. Thus, recycling the carbon tax revenues to reduce the CIT might have played a major role in how emissions are reduced in the manufacturing sector, possibly through investments.

[53] Although not statistically significant, 0.2 amounts to 4% of the average exits in BC's industries.

Table 7 Estimates for Selection Effects

	Exit		Entry	
	(1)	(2)	(3)	(4)
$K_p \times D_t \times EI_{jp}$	0.56	0.20	2.74	3.06**
	(0.73)	(0.66)	(1.88)	(1.32)
Sub-sector × time		Y		Y
N	5,939	5,939	5,920	5,920
R^2	0.77	0.80	0.78	0.81

Dependent variable is the number of exiting or entering plants. EI_{jp} is the average emission intensity for industry-province pair from the pre-policy period. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. All specifications include industry by province FEs, high emission intensive industry by time FEs, province by time FEs. Columns (2) and (4) include subsector (3-digit NAICS) by time FEs. To account for serial correlations, standard errors are clustered by province by industry (4-digit NAICS), reported in parentheses

***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

Table 8 Decomposition of Aggregate Emission Effects

Scale Effect	Technique Effect	Selection Effect		Interaction Effect	Total
		Exit	Entry		
1.7%	−5.67%	−0.0026%	0.03%	−0.096%	−4.04%

This table shows the scale, technique, selection, and interaction effects of the aggregate emission change. Column 5 reports the total effect

Finally, we use the plant-level estimates found in this paper to quantify the effect of the policy on aggregate emissions. We find that a reduction of aggregate emissions comes from the intensive margin adjustments (i.e., the scale and technique effects) of the surviving plants to the policy. Plant entries and exits in response to BC carbon tax are limited.

What would be important to investigate in future research is the long-run effect of the policy. This paper has already demonstrated the importance of the technique effect for emission reductions in response to the policy. Many argue that it takes time for investments to substantially impact emission reductions, productivity enhancement, or even both. Thus, investigating the long-run effect of this policy would provide a fruitful contribution to both the literature and public policy. Furthermore, we could better understand the magnitude of each component of a revenue-neutral carbon tax by identifying the emission effect from the carbon tax and CIT reduction separately.

Appendix A: Model

In this appendix, we show that the size of the technique and scale effects also depends on a plant's emission intensity and that the signs are also ambiguous. Totally differentiating Eqs. (3.15) and (3.16) with respect to the carbon tax yield:

$$\begin{aligned}\frac{de}{d\tau} &= \underbrace{\left(\frac{\alpha}{\gamma}-1\right)\frac{e}{\tau}}_{\gtreqless 0} + \underbrace{\left(\frac{\beta(1-\alpha)}{\gamma}\right)\frac{e}{1+t^{\mathrm{METR}}}}_{(+)}\underbrace{\frac{d(1+t^{\mathrm{METR}})}{d\tau}}_{(-)} \\ &= \left[\frac{\alpha[1-\rho(1-\sigma)]+\varepsilon\beta(1-\alpha)-1}{\gamma}\right]\frac{ex}{\tau}\end{aligned} \tag{A.1}$$

$$\begin{aligned}\frac{dx}{d\tau} &= \underbrace{\left(-\frac{\alpha\sigma}{\gamma}\right)\frac{z}{\tau}e^{-1}}_{(-)} + \underbrace{\left(-\frac{\beta(1-\alpha)\sigma}{\gamma}\right)\frac{z}{1+t^{\mathrm{METR}}}e^{-1}}_{(-)}\underbrace{\frac{d(1+t^{\mathrm{METR}})}{d\tau}}_{(-)} \\ &= \left[\frac{-\sigma[\alpha+\varepsilon\beta(1-\alpha)]}{\gamma}\right]\frac{z}{\tau}e^{-1}\end{aligned} \tag{A.2}$$

Similar to Eqs.(3.18), (A.1) and (A.2) are both a function of a plant's emission intensity. As the signs of these equations are ambiguous due to the same reason as Eq. (3.18), these provide a motivation for the estimation equation for the technique and scale effects in Sect.5.4.

Appendix B: Additional Results

In this appendix, we present additional results discussed in the main text.

B.1 Difference-in-Differences Estimations

As an alternative to Eqs. (4.1) and (5.1), one can estimate a more conventional DID estimator, i.e., compare plants in BC with plants in the rest of Canada before and after the policy:

$$\ln E_{lipt} = \beta(K_p \times D_t) + \alpha_l + \phi_{i't} + \epsilon_{lipt} \tag{B.1}$$

where all is defined as in Eq. (4.1). While this approach is intuitive and simple, it is difficult to isolate the causal effect of the policy on emission responses, especially when other concurring events happened along with the implementation of the policy, such as the Great Recession. If these confounding factors affect plants in different provinces in the same way, the fixed effects would take care of biases from these factors. Unfortunately, we imagine that the Great Recession had differential impacts across provinces because provinces have different industrial compositions, have access to different international markets, and because some provinces are natural resource-based economies (i.e., Alberta, Saskatchewan, and Manitoba encounter less impact from the recession). To mitigate this issue, we directly exploit the variation in the plant-level policy exposure using the emission intensity in Eq. (4.1). This allows us to include the fixed effects at a more granular level, possibly capturing differential effects of the Great Recession across provinces and industries.

Table 9 reports the results from estimating Eq. (B.1), columns (1) and (2). In addition to the DID estimator explained above, we also estimate two other DID estimators. First, we compare the high emission-intensive and low emission-intensive plants in BC only. This would address the bias from the differential shocks across provinces but would suffer from the differential shocks between high emission-intensive and low emission-intensive plants. The results of this DID are reported in columns (3) and (4) of Table 9. Second, we only use the high emission-intensive plants, allowing us to compare the high emission-intensive plants in BC with those in the rest of Canada before and after the policy, reported in columns (5) and (6) of Table 9. Conversely, this would address the bias from the differential shocks between the high emission-intensive and low emission-intensive plants, but would suffer from the differential province shocks. Although most point estimates are not statistically different from zero, they all suggest that the carbon tax reduces manufacturing emissions. This is consistent with the findings discussed below. As pointed out by Yamazaki (2017), the lack of statistical significance in Table 9 could be due to the lack of variation in

Table 9 Difference-in-differences Estimates for Emissions

	(1)	(2)	(3)	(4)	(5)	(6)
$K_p \times D_t$	−0.06	−0.053			−0.11*	−0.08
	(0.05)	(0.06)			(0.058)	(0.07)
$EI_l \times D_t$			−0.2	−0.28		
			(0.23)	(0.13)		
Plant	Y		Y		Y	
City × industry		Y		Y		Y
Measurement error correction		Y		Y		Y
N	117,445	42,459	13,946	5,194	35,227	13,373
R^2	0.90	0.93	0.92	0.94	0.90	0.93
Sample	Full		Only BC		Only high EI	

Dependent variable is log of plant-level emission. EI_l is the average emission intensity for plant l from the pre-policy period. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Industry refers to the 6-digit NAICS industry while sector refers to the 2-digit NAICS industry. All specifications include sector by time FEs. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (at 2-digit NAICS), reported in parentheses. Columns (1) and (2) use the full sample, while columns (3) and (4) use only plants in BC, comparing high emission-intensive plants with low emission-intensive plants before and after the policy within BC. Columns (5) and (6) use only high emission-intensive plants, comparing high emission-intensive BC plants with high emission-intensive non-BC plants before and after the policy. Measurement error correction is applied to columns (2), (4), and (6). For these specifications, the dependent variable is log of city by industry-level emission and EI_l is replaced with EI_{cip}. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level the treatment variables to precisely estimate the emission effect, which is why Eq. (4.1) is important for the identification.

B.2: Testing the Robustness with Different Threshold Levels for High Emission Intensive Plants

In estimating Eq. (4.1), we arbitrarily choose the 70th percentile of plant-level emission intensity as a threshold for the high emission-intensive plant by year FEs. We explore the robustness of our main estimates by using the different threshold levels, i.e., 50th, 60th, and 80th percentiles. The results are presented in Table 10.

Columns (1) and (2) are taken from columns 5 and 6 of Table 3. The rest of the columns explore the different threshold levels. The first impression from these results is that the main estimates are robust to the different threshold levels, i.e., the coefficients are statistically significant and negative.

Table 10 Different Threshold Levels for High Emission Intensive Plants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$K_p \times D_t \times EI_{cip}$	−0.26**	−0.23**	−0.32***	−0.28**	−0.29***	−0.25**	−0.23**	−0.21**
	(0.10)	(0.10)	(0.11)	(0.12)	(0.11)	(0.11)	(0.09)	(0.1)
Sector × time		Y		Y		Y		Y
High emission intensive plant × time								
70th percentile	Y	Y						
50th percentile			Y	Y				
60th percentile					Y	Y		
80th percentile							Y	Y
N	41,548	41,548	41,548	41,548	41,548	41,548	41,548	41,548
R^2	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93

Dependent variable is log of city by industry-level emission. EI_{cip} is the average pre-policy emission intensity for city c, industries i, and province p. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Industry refers to the 6-digit NAICS industry while sector refers to the 2-digit NAICS industry. All specifications include city by sector FEs and province by time FEs, and the measurement error correction is applied to all. Columns (1) and (2) are taken from columns (3) and (4) of Table 3. In columns (3) ~ (8), we changed the threshold level for high emission intensive plant by time FEs. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (at 2-digit NAICS), reported in parentheses. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

Table 11 Different control groups: Provinces with limited trade with BC

	Emission		Output		Emission intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
$K_p \times D_t \times EI_{cip}$	−0.27***	−0.247***	0.084***	0.086***	−0.35***	−0.33***
	(0.081)	(0.083)	(0.028)	(0.027)	(0.084)	(0.085)
Sector × time		Y		Y		Y
N	11,794	11,794	11,794	11,794	11,794	11,794
R^2	0.94	0.94	0.96	0.96	0.82	0.82

Dependent variable is log of city by industry-level emission. EI_{cip} is the average pre-policy emission intensity for city c, industries i, and province p. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. It includes high emission intensive plant by time FEs, province by time FEs, sector (2-digit NAICS) by time FEs, and city by industry (6-digit NAICS) FEs. The measurement error correction is applied to all the specifications. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (2-digit NAICS), reported in parentheses. The selected provinces are Newfoundland and Labrador, Prince Edward Island, Nova Scotia, New Brunswick, Manitoba, and Saskatchewan. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level

B.3: Indirect Test of SUTVA

One of the important assumptions for the identification is the SUTVA. As discussed in the main texts, this could be violated by the general equilibrium (GE) effects through the inter-provincial trades of intermediate goods. From a cost pass-through, it would make it more expensive for plants in other provinces to produce with the imported intermediate goods from BC. The magnitude of this change depends on the bilateral trade cost. The control group being (indirectly) affected by the policy violates the SUTVA. To test the severity of this concern, we re-estimate Eq. (4.1) using only provinces that have very low trade flows with BC. The selected provinces are Newfoundland and Labrador, Prince Edward Island, Nova Scotia, New Brunswick, Manitoba, and Saskatchewan.

Table 11 shows that the estimates are similar to those in the main text, i.e., they are statistically significant and negative. The magnitudes are also similar. These results provide a piece of evidence that the violation of the SUTVA through the GE effects is not warranted.

B.4 Indirect Test of Price Effect for Scale Effect Analysis

In Sect. 5.4, we explore the scale effect of the emission responses to a carbon tax, i.e., emission falls from the output decline. We implicitly assume that the prices are stable. We indirectly explore this by interacting our main treatment variable with subsector trade

Table 12 Interaction with industry trade intensity

$\ln Q$	(1) Plant-level	(2) MEC
$K_p \times D_t \times EI_l$		
$\times$ High trade-intensive$_i$	0.03	0.123***
	(0.04)	(0.03)
$\times$ Medium trade-intensive$_i$	0.15	0.019
	(0.11)	(0.108)
$\times$ Low trade-intensive$_i$	−0.74	−0.46
	(0.747)	(0.77)
N	117,445	41,548
R^2	0.95	0.96

Dependent variable is log of plant-level output. EI_l is the average emission intensity for plant l from the pre-policy period. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Both specifications include high emission intensive plant by time FEs, province by time FEs, and sector (2-digit NAICS) by time FEs. Plant-level estimates includes the plant FEs while the MEC estimates includes city by industry (6-digit NAICS) FEs. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (2-digit NAICS), reported in parentheses. High trade-intensive subsectors are 327, 323, 337, 321, 332, 324, and 312. Medium trade-intensive subsectors are 311, 339, 326, 322, 325, 331, and 336. Low trade-intensive subsectors are 333, 314, 313, 316, 315, 334, and 335. Please refers to Table 14 for the corresponding NAICS codes. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level intensity. The results are presented in Table 12. We show that the coefficient shown in Table 3 is fairly close to the coefficient for highly trade-intensive subsectors in Table 12, implying that our assumption on price effect may be justified.

B.5: Robustness Check with Matching (Re-Weighting) Method

Despite the advantage of the augmented DID method, one can even take one step further to ensure the credibility of the main estimates by combining regression and the matching method. To best utilize our rich confidential dataset, we do this by re-estimating Eq. (4.1) with weights based on the estimated propensity-scores. This would ensure the similarity between treated and control plants as well as overcome the issue of the

Table 13 Baseline estimates with the propensity-scores weighted method

	Plant-level		City by industry-level	
	(1)	(2)	(3)	(4)
$K_p \times D_t \times EI_l$	−0.25**	−0.38***		
	(0.10)	(0.07)		
$K_p \times D_t \times EI_{cip}$			−0.18*	−0.27***
			(0.09)	(0.05)
Plant	Y	Y		
City × industry			Y	Y
Controls		Y		Y
MEC			Y	Y
N	90,402	77,153	40,990	26,940
R^2	0.93	0.94	0.94	0.95

Dependent variable for columns (1) and (2) is log of plant-level emission while that for columns (3) and (4) is log of city by industry-level emission. EI_l is the average pre-policy emission intensity for plant l, while EI_{cip} is the average pre-policy emission intensity for city c, industries i, and province p. D_t is a dummy for the post-policy period, which is equal to one after 2008 and is equal to zero otherwise. K_p is a dummy variable that takes the value of one for BC and zero for all other provinces. Industry refers to the 6-digit NAICS industry while sector refers to the 2-digit NAICS industry. Columns (2) and (4) include additional controls, i.e., plant's age, input-output ratio, the number of plants owned by the parental firm, and export volume. MEC stands for measurement error correction. All specifications include high emission intensive plant by time FEs, province by time FEs, and sector by time FEs. To account for serial correlations and within sector correlations, standard errors are clustered by province by sector (at 2-digit NAICS), reported in parentheses. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level curse of dimensionality in other matching methods. We estimated the propensity-scores with many plant characteristics, such as output, labor, energy, export volume, industry type, total expenditure, total revenues, and R&D expenditure. The results are presented in Table 13.

Columns (1) and (2) are equivalent to columns (2) and (4) in Table 3, while columns (3) and (4) are equivalent to columns (6) and (8) in Table 3. There are two important remarks worth discussing from this. First, the estimates are considerably similar to those in Table 3. Second, the point estimate in column (1) is now statistically significant when the point estimate in column (2) in Table 3 is not. This implies that even at the plant-level analyses, there is a negative emission effect in response to the carbon tax. This provides, not only robust findings, but also convincing support for the main estimates.

B.6: Decomposition

In Sect. 6, we derived the empirical analogue of the manufacturing emission given by Eq. (6.2). We heavily follow Najjar and Cherniwchan (2021) and show more algebraic steps to get to Eq. (6.3) and explain how we can use the estimates presented in this paper to discuss the aggregate emission response to the policy.

We start from the equation for the change in manufacturing emission between $t-1$ and t:

$$\begin{aligned}\Delta Z_{mt} = &\int_0^{n_{mt}} x_{mt}(n)e_{mt}(n)dn - \int_0^{n_{mt}} x_{mt-1}(n)e_{mt-1}(n)dn\\ &+\int_{n_{mt}\in\, n^{\text{Enter}}} x_{mt}(n)e_{mt}(n)dn - \int_{n_{mt}\in\, n^{\text{Exit}}} x_{mt-1}(n)e_{mt-1}(n)dn\end{aligned}$$

This can be rewritten as:

$$\begin{aligned}\Delta Z_{mt} = &\int_0^{n_{mt}} (x_{mt}(n)-x_{mt-1}(n))e_{mt}(n)dn + \int_0^{n_{mt}} x_{mt-1}(n)(e_{mt}-e_{mt-1}(n))dn\\ &+\int_0^{n_{mt}} (x_{mt}(n)-x_{mt-1}(n))e_{mt-1}(n)dn - \int_0^{n_{mt}} (x_{mt}(n)-x_{mt-1}(n))e_{mt-1}(n)dn\\ &+\int_{n_{mt}\in\, n^{\text{Enter}}} x_{mt}(n)e_{mt}(n)dn - \int_{n_{mt}\in\, n^{\text{Exit}}} x_{mt-1}(n)e_{mt-1}(n)dn\end{aligned}$$

Then, with further algebra, this reduces to:

$$\begin{aligned}\Delta Z_{mt} = &\int_0^{n_{mt}} \Delta x_{mt}(n)e_{mt-1}dn + \int_0^{n_{mt}} x_{mt-1}(n)\Delta e_{mt}(n)dn\\ &+\int_{n_{mt}\in\, n^{\text{Enter}}} x_{mt}(n)e_{mt}(n)dn - \int_{n_{mt}\in\, n^{\text{Exit}}} x_{mt-1}(n)e_{mt-1}(n)dn\\ &+\int_0^{n_{mt}} \Delta x_{mt}(n)\Delta e_{mt}(n)dn\end{aligned}$$

Finally, dividing this by Z_{mt-1} yields our empirical decomposition, given by Eq. (6.3) in the main text.

Next, we show how we can use our estimates presented in the paper in Eq. (6.3). Again, following Najjar and Cherniwchan (2021), $\dot{x}_{mt}(n)$ and $\dot{e}_{mt}(n)$ can be calculated as:

$$\dot{x}_{mt}(n) = \begin{cases} \hat{\beta}_x, & \text{if plant n is treated} \\ 0, & \text{otherwise} \end{cases} \qquad \dot{e}_{mt}(n) = \begin{cases} \hat{\beta}_e, & \text{if plant n is treated} \\ 0, & \text{otherwise} \end{cases}$$

where $\hat{\beta}_x$ and $\hat{\beta}_e$ are causal estimates of the average change in plant output and emission intensity due to the policy, respectively. They are the estimates presented in Sect. 5.4. Letting the share of the manufacturing emission at $t-1$ from treated plants be given by $\eta_{mt-1}^{\text{Treated}} = \int_{n \in \text{Treated}} \eta_{mt-1}(n)dn$, the scale (SC) and technique (TE) effects can be expressed as:

$$\widehat{\text{SC}} = \hat{\beta}_x \eta_{mt-1}^{\text{Treated}}, \qquad \widehat{\text{TE}} = \hat{\beta}_e \eta_{mt-1}^{\text{Treated}}$$

To construct an expression for the selection effect, $\int_{n_{mt} \in\, n^{\text{Entry}}} \frac{z_{mt}(n)}{Z_{mt-1}} dn - \int_{n_{mt} \in\, n^{\text{Exit}}} \eta_{mt-1}(n)dn$, we need estimates of the policy's effects of the plant entries and exits and information on the average emission share of the entering and exiting plants. In Sect. 6, we present causal estimates of the average plant entries and exits in response to the policy, denoting it as $\hat{\beta}_{\text{Entry}}$ and $\hat{\beta}_{\text{Exit}}$. Then, the selection (SE) effect can be expressed as:

$$\widehat{\text{SE}} = \hat{\beta}_{\text{Entry}} \overline{\eta}_{mt}^{\text{Entry}} - \hat{\beta}_{\text{Exit}} \overline{\eta}_{mt-1}^{\text{Exit}}$$

where $\overline{\eta}_{mt}^{\text{Entry}}$ and $\overline{\eta}_{mt-1}^{\text{Exit}}$ are the average entering and exiting plants' share of manufacturing emission, respectively.

Lastly, the interaction effect in Eq. (6.3) can be expressed by substituting the estimates for $\dot{x}_{mt}(n)$ and $\dot{e}_{mt}(n)$ as:

$$\widehat{\text{IE}} = \hat{\beta}_x \hat{\beta}_e \eta_{mt-1}^{\text{Treated}}$$

Putting all these together, we have:

$$\dot{Z}_{mt} = \underbrace{\hat{\beta}_x \eta_{mt-1}^{\text{Treated}}}_{\text{SC}} + \underbrace{\hat{\beta}_e \eta_{mt-1}^{\text{Treated}}}_{\text{TE}} + \underbrace{\hat{\beta}_{\text{Entry}} \overline{\eta}_{mt}^{\text{Entry}} - \hat{\beta}_{\text{Exit}} \overline{\eta}_{mt-1}^{\text{Exit}}}_{\text{SE}} + \underbrace{\hat{\beta}_x \hat{\beta}_e \eta_{mt-1}^{\text{Treated}}}_{\text{IE}}$$

Appendix C: Data

In this appendix, we present additional information about our data.

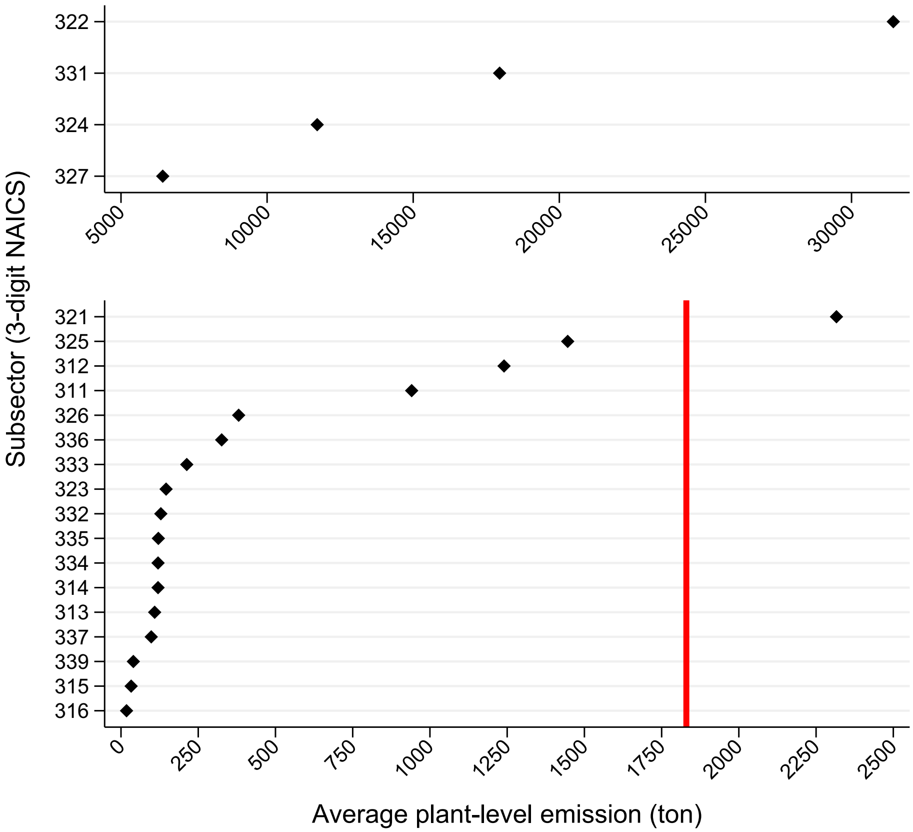
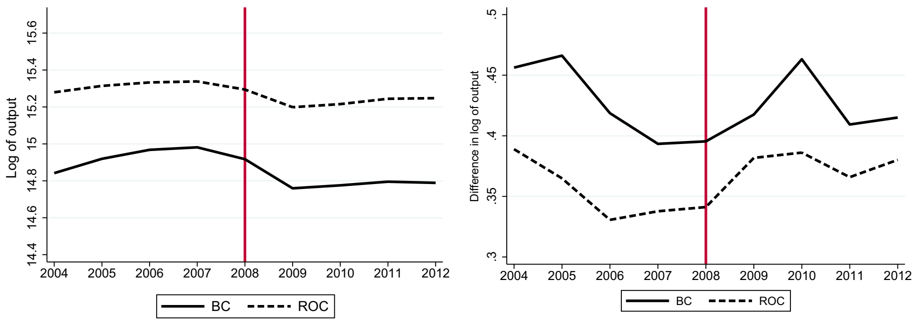


Fig. 6 This figure plots a distribution of average plant-level emission across subsectors (3-digit NAICS). The solid red line represents the average plant-level emission among all subsectors



(a) Average outputs **(b)** Differences in average outputs

Fig. 7 This figure plots output trends for BC and ROC. Panel (**a**) presents the trends of average output for BC and ROC, while Panel (**b**) presents the trends of differences in average outputs between high and low emission intensive plants for BC and ROC

Table 14 Manufacturing Industries at 3-digit NAICS code

311	Food manufacturing
312	Beverage and tobacco product manufacturing
313	Textile mills
314	Textile product mills
315	Clothing manufacturing
316	Leather and allied product manufacturing
321	Wood product manufacturing
322	Paper manufacturing
323	Printing and related support activities
324	Petroleum and coal product manufacturing
325	Chemical manufacturing
326	Plastics and rubber products manufacturing
327	Non-metallic mineral product manufacturing
331	Primary metal manufacturing
332	Fabricated metal product manufacturing
333	Machinery manufacturing
334	Computer and electronic product manufacturing
335	Electrical equipment, appliance and component manufacturing
336	Transportation equipment manufacturing
337	Furniture and related product manufacturing
339	Miscellaneous manufacturing
311	Food manufacturing
312	Beverage and tobacco product manufacturing
313	Textile mills
314	Textile product mills
315	Clothing manufacturing
316	Leather and allied product manufacturing
321	Wood product manufacturing
322	Paper manufacturing
323	Printing and related support activities
324	Petroleum and coal product manufacturing
325	Chemical manufacturing
326	Plastics and rubber products manufacturing
327	Non-metallic mineral product manufacturing
331	Primary metal manufacturing
332	Fabricated metal product manufacturing
333	Machinery manufacturing
334	Computer and electronic product manufacturing
335	Electrical equipment, appliance and component manufacturing
336	Transportation equipment manufacturing
337	Furniture and related product manufacturing
339	Miscellaneous manufacturing

Table 15 Size of output and emission intensity in BC

Emission intensity (percentile)	Output ($1K)
Below 10th percentile	4,877
Between 10th and 25th percentile	3,577
Between 25th and 50th percentile	3,141
Between 50th and 75th percentile	4,156
Between 75th and 90th percentile	5,666
Above 90th percentile	6,388

This shows the size of output for 6 categories based on the emission intensity percentile in BC

Table 16 Summary statistics

	Canada		BC	
	Dropped	In-sample	Dropped	In-sample
Output ($ millions)	11.89	15.71	7.93	8.39
	(119)	(153)	(20)	(35)
Labor expenses ($ millions)	2.71	9.26	4.46	4.46
	(4.8)	(4.5)	(0.6)	(0.6)
# of salary worker	3.9	11.6	3.3	7.1
	(16.19)	(42.04)	(9.81)	(20.04)
# of production worker	11.27	34.32	9.98	23.38
	(48.42)	(114)	(25.48)	(58.97)
Plant age	8.04	7.17	7.95	6.98
	(3.04)	(3.35)	(3.10)	(3.40)
Total expense ($ millions)	13.92	17.98	8.35	9.25
	(174)	(163)	(20.4)	(46.4)

This shows summary statistics for key variables. In the main text, we mentioned that we excluded some plants as they do not report their energy expenditure. We denote Dropped as those plants dropped from the data while In-sample indicates those plants that are kept in the data for the estimation. We show a summary statistics for Canada and BC

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