Asymmetric Environmental Regulation, Interfuel Substitution and Carbon Leakage*

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This Version: *June 6, 2025*

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Abstract

This paper studies how plants reorganize their production when faced with asymmetric carbon pricing. While plants may compete with each other across geographical regions, some regions may have carbon pricing policies while others do not. Asymmetric regulation can lead to carbon leakage, shifting emissions from regulated to unregulated areas. I build a model of imperfect competition with multiple fuels as energy inputs, which allows for region-specific carbon taxes. Using publicly available Canadian plant-level data on a wide range of air pollutants, I invert the chemical reaction from combustion to back out plants' fuel usage. I then estimate the model by exploiting the British Columbia (B.C.) and Quebec carbon taxes implemented in 2008 and 2007, respectively. Findings indicate substantial emissions reductions in British Columbia, with 95% confidence intervals ranging from 15% to 35%, and moderate reductions in Quebec. Contrary to theoretical predictions of carbon leakage, the analysis reveals no statistically significant shift in production towards unregulated provinces. A detailed decomposition highlights that the absence of leakage was primarily due to regulated plants' ability to absorb the tax by switching from oil to natural gas and due to aggregate price increases, which suppressed overall consumer demand and inhibited the ability of unregulated plants to increase output.

*Special thanks to David Rivers, Nouri Najjar, and Jevan Cherniwchan for their helpful comments and guidance throughout the elaboration of this project. I also want to thank participants at the 2019 Canadian Economic Association Conference (CEA) for their valuable comments. All errors are my own.

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1 Introduction

Many countries are implementing regulations to combat pollution and its associated environmental challenges. As a result, there is an increasing interest in assessing the effectiveness of these policies in reducing pollution. The combustion of fossil fuels, a major contributor to pollution, creates a negative externality through the emission of greenhouse gases that contribute to global warming. Under Pigouvian theory, the optimal policy for addressing this externality is a carbon tax equal to the marginal social damages of GHG emissions. Although many countries and regions have implemented carbon taxes, the limited jurisdictional scope of regulation is such that even the most ambitious pollution reduction programs, such as the Kyoto Protocol and the Paris Agreement, are voluntary, and their effectiveness depends on the goodwill of governments. In this context, there is a risk of "carbon leakage", where emissions shift to unregulated regions as a result of asymmetric regulation.

This risk of carbon leakage is particularly relevant in the context of manufacturing activity because firms are known to compete across regions (Smith and Ocampo, 2020). Moreover, manufacturing activity contributes to 37% of global greenhouse gas emissions (Worrell, Bernstein, Roy, Price and Harnisch, 2009) and is one of the primary targets of carbon taxes.

Concerns about carbon leakage are accentuated in the case of sub-national and even sub-union regulation because production is more likely to shift across borders within a country/union due to lower trade barriers. Moreover, while carbon leakage is an interesting phenomenon, its presence biases empirical studies that estimate the direct effect of carbon taxes. Indeed, the possibility of cross-region competition makes it more difficult to exploit the jurisdictional boundaries of policies as natural experiments to form counterfactuals because it implies that the policy also treats unregulated plants. To use standard policy evaluation tools such as Difference-in-Difference to recover the effect of a policy, one must then make strong independence assumptions that rule out carbon leakage.

In this paper, I study carbon leakage in the context of the British Columbia (B.C.) and Quebec carbon taxes implemented in 2007 and 2008, respectively. Quebec introduced a modest $\$3.50/tCO_{2e}$ carbon tax levied on fossil fuels in 2007, which it phased out by 2015 as it moved to a cap-and-trade system jointly with California. British Columbia followed in July 2008 with a revenue-neutral, province-wide carbon tax that started at CA $\$10/t$ and increased by $\$5/t$ each July to $35/t$ by 2013, remaining frozen at that level through 2016.

I build a heterogeneous plants model with monopolistic competition, multiple regions, and multiple industries similar to Shapiro and Walker (2018) and Aichele and Felbermayr (2015). In the model, a carbon tax increases regulated plants' marginal costs, making them less competitive than unregulated plants. The increase in marginal costs depends on plants' capacity to substitute cleaner fuels for dirty fuels, and the extent of carbon leakage depends on the willingness of consumers to substitute across differentiated plants. The model allows me to study both the direct effects of the carbon tax in regulated regions and the leakage effect in unregulated regions. Most importantly, I provide identification results to quantify this model—and, by extension, carbon leakage—using publicly available emissions data/remote sensing data only.

I use publicly available Canadian data on a wide range of pollutants emitted in the air by manufacturing establishments, along with detailed fuel emissions factors provided by EPA's "AP-42: Compilation of Air Emissions Factors for Stationary Sources" (U.S. Environmental Protection Agency, 2024a). These data allow me to invert chemical reactions from fuel combustion to estimate plants' usage of different fossil fuels. I then estimate the model's parameters by exploiting variation in the B.C. and Quebec carbon taxes before Canada implemented its nationwide carbon tax in 2018. Key parameters include the oil-gas elasticity of substitution and the elasticity of demand.

I find substantial emissions reductions in British Columbia, averaging 24% between 2008 and 2016 with 95% confidence intervals ranging from 15% to 35%, and moderate reductions in Quebec. Contrary to theoretical predictions of carbon leakage, the analysis reveals no statistically significant shift in production towards unregulated provinces. A detailed decomposition highlights that the absence of leakage was primarily due to regulated plants' ability to absorb the tax by switching from oil to natural gas and due to aggregate price increases, which suppressed overall consumer demand and inhibited the ability of unregulated plants to increase output despite becoming relatively more competitive. More precisely, I cannot reject the hypothesis that output varieties are gross complements against the alternative of gross substitutes. I also find that the carbon tax caused an average output reduction of 10% among B.C. plants, but no statistically significant impact on profits. Regulated plants passed through part of the cost increase to consumers.

The model features monopolistic competition in the spirit of Melitz (2003a) and multiple regions. In a nontrivial extension of Copeland and Taylor (2004), I allow multiple fossil fuels to be used in production and specify pollution as a byproduct of fossil fuel combustion. Following recent literature on fuel substitution, I also enable plants to use different fuel sets, such as oil with gas, gas only, and oil only (Murray Leclair, 2024; Kaartinen and Prane, 2024). Fossil fuel combustion generates energy for production but also releases greenhouse gases (GHG) into the atmosphere. This production function thus directly maps to emissions and carbon tax data. Carbon taxes are implemented with a per-unit tax rate on various fuels, and vary based on the different emission intensity of each fuel. The tax increases the cost of using dirtier relative to cleaner fuels [1].

This extension allows me to identify and estimate the model's parameters and provide novel empirical evidence on carbon leakage using only publicly available pollution release/remote sensing data, fuel price data, and industry aggregates, all of which are commonly available. The key to my method is that, under a standard set of assumptions about plants' production processes and profit maximization, pollution data contains information about which fuels plants use, how much of each fuel they use, and some information about each firm's scale of production relative to other plants.

I exploit the B.C. and Quebec carbon taxes to identify the model's parameters. I assume that the production technology features constant elasticity of substitution (CES) between different fuels, and I separate identification into two parts. The first part comes from each plant's cost minimization problem of choosing relative fuel quantities to form a composite fuel index. I show closed-form identification of reduced-form parameters that directly map into structural technology parameters from variation in the *relative* tax rate between fuels: fuel-specific efficiency parameters that can flexibly vary across plants and the interfuel elasticity of substitution. The second part comes from each plant's profit maximization problem, in which they choose output quantity subject to a given level of the composite fuel index. I now observe an estimate of plants' fuel composite input, which contains information about their productivity. I leverage variation in the *level* of the carbon tax to identify the elasticity of substitution across plants.

The data I use is the National Pollutant Release Inventory (NPRI) (Environment and Climate Change Canada, 2025) combined with industry-level aggregates. The former contains all pollutants released by manufacturing plants in Canada. I specifically use pollutants released in the air known to come from the combustion of specific fossil fuels. I invert each fuel's chemical reaction to recover an estimate of fuel quantities from a range of pollutants. This procedure is key because the model relies on plant-level fuel quantities to identify the effect of carbon taxes.

My method applies to contexts with abundant remote sensing data but where plant-level data is difficult to access or hardly even exists. It also contributes to a growing literature on carbon

[1] Many carbon taxes translate to a per-unit fuel tax in practice, including the B.C. and Quebec carbon taxes.

leakage with a longstanding theoretical foundation (Garella and Trentinaglia, 2019; Holland, 2012; Hoel, 1991) and computational general equilibrium (CGE) applications (Böhringer, Carbone and Rutherford, 2016; Felder and Rutherford, 1993). More closely related is the work of Dechezleprêtre et al. (2022) and Ben-David et al. (2021), who empirically study carbon leakage from multi-plant and multinational firms. Within-firm leakage is the most likely type of carbon leakage because firms can make coordinated decisions across jurisdictions. I complement this literature by looking at carbon leakage between competing plants, where leakage results from the increase in competitiveness of unregulated plants relative to regulated plants. I provide one of the first empirical assessments of this competitive channel for carbon leakage.

Moreover, since carbon tax rates are heterogeneous by fuel types, I allow plants to substitute across different fuels. Similar to the approaches of Atkinson and Luo (2023), Ganapati, Shapiro and Walker (2020), and Carlson, Burtraw, Cropper and Palmer (2000), fuel substitution provides an endogenous margin of pollution intensity adjustment. Results on the elasticity of substitution are consistent with previous literature on interfuel substitution that overwhelmingly suggests that fuels are gross substitutes. In this paper, I find an oil-gas micro-elasticity of substitution between 1.4 and 2.1, depending on the specification. Papageorgiou et al. (2017) find that the elasticity of substitution between clean and dirty energy inputs is significantly greater than 1, and goes up to 3 in non-electricity sectors. Similarly, Jo (2024) finds a micro-elasticity of substitution between clean and dirty energy inputs between 1.4 and 3.1.[2] An earlier meta-analysis by Stern (2012) finds similar results, emphasizing the importance of the oil-gas substitution. They also discuss the importance of the substitution between fossil fuels and electricity. While I cannot directly investigate electrification, I discuss this channel in Section 6.2.

Section 2 presents the intuition underlying carbon leakage. Section 3 presents the model in all its details. Section 4 presents the data. Section 5 presents identification details and estimation results. Section 6 presents counterfactuals of interests and decomposes the effect of carbon taxes. Lastly, Section 6.2 discusses various extensions and robustness to potential criticisms.

[2]The micro-elasticity of substitution refers to the elasticity of substitution within establishments, as opposed to the aggregate elasticity, which also accounts for output reallocation from dirty to clean establishments.

2 Carbon leakage mechanisms

In this section, I explain intuitively the different mechanisms through which an asymmetric carbon tax can lead to carbon leakage, which is presented in Figure 1. Two mechanisms induce leakage by making unregulated plants more competitive. One is at the intensive margin and the other is at the extensive margin (through entry and exit). First, the carbon tax increases regulated plants' marginal cost, resulting in a higher output price. Regulated plants become relatively less competitive than unregulated plants, demand shifts accordingly, and output reallocates across regions. Second, the increase in marginal costs can increase the productivity required for plants to be profitable, forcing some regulated plants to exit the market. At the same time, the gain in competitiveness in unregulated regions lowers the productivity required for plants to be profitable, inducing entry in those regions.

The extent to which regulated plants can substitute for dirty fuels will mitigate both sources of carbon leakage by mitigating the negative impact of the tax on marginal costs. Figure 1 indicates this substitution channel in blue. In general equilibrium, such variation in relative fuel demand will increase the spot market price of clean relative to dirty fuels. Unregulated plants now face lower relative prices of dirty fuels, which could induce unintended substitution towards dirty fuels.

In Figure 1, I highlight in a gray box the channels considered in this paper. I abstract from both general equilibrium and entry/exit. First, Canadian plants are too small relative to the rest of the world to significantly impact aggregate fuel demand and induce changes in world spot market fuel prices. Second, preliminary evidence suggests that the carbon taxes did not cause firm exit in regulated regions. Difference-in-difference (DiD) estimation on the number of plants operating in each province due to the B.C. and Quebec carbon taxes suggests an increase in the number of plants operating in both regulated provinces, which is at odds with theoretical predictions. See Appendix A.1 for details. This result is not innocuous, especially for British Columbia. It is consistent with previous evidence that the B.C. carbon tax fostered a slight increase in aggregate employment due to its revenue neutrality (Yamazaki, 2017, 2022).

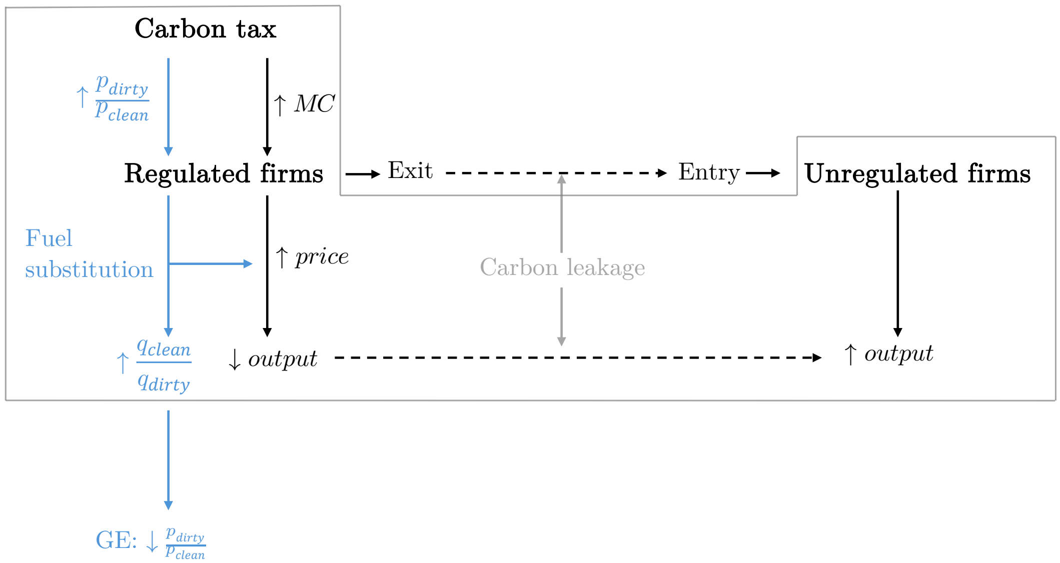


Figure 1: Carbon Leakage Channels

Notes: This figure shows the main channels through which an asymmetric carbon tax can cause carbon leakage. The carbon tax increases regulated plants' marginal cost, which makes unregulated plants relatively more competitive. However, the extent to which a carbon tax causes an increase in marginal costs depends on the ability of regulated plants to substitute away from dirty fuels, which I show with the perpendicular blue line.

3 Model

3.1 Structure of the Economy

The economy features plants in multiple industries that produce differentiated varieties and engage in monopolistic competition across multiple regions. It shares similarities with Shapiro and Walker (2018) and Melitz and Redding (2014). I augment this framework with plant-specific production functions that take different fuels as inputs and can substitute between them. I introduce an asymmetric carbon tax that only affects plants in specific regions to study carbon leakage. I will present the main framework for a single region. I will give details on multiple regions after introducing the asymmetric carbon tax. A Cobb-Douglas aggregator takes the output of J industries and aggregates them into a final good:

$$Y = \prod_{j=1}^{J} Y_j^{\beta_j} \text{ with } \sum_j \beta_j = 1.$$

β_j is the share of industry j's production allocated to final consumption. The final good producer chooses how much of each industry's aggregate is needed to maximize some fixed amount of final consumption subject to a standard budget constraint: $\sum_j P_j Y_j = C$ where C denotes aggregate income. Throughout the paper, I assume that aggregate income is in dollar units and that plants take it as given. The solution to this problem is standard and yields the share of total consumption produced by each industry, $Y_j = \frac{\beta_j}{P_j} C$. Next, within each industry, plants indexed by i sell differentiated goods indexed Y_{ij}, which can be substituted at a rate $\rho > 1$ to form the CES composite industry output Y_j. This problem yields a standard CES demand function with elasticity of demand ρ, a crucial parameter for carbon leakages. It determines how easily consumers can substitute the output of unregulated plants for regulated plants:

$$Y_{ij} = \left(\frac{P_{ij}}{P_j}\right)^{-\rho} Y_j, \tag{1}$$

where $P_j \equiv \left(\int_{\Omega_j} P_{ij}^{(1-\rho)} di\right)^{1/(1-\rho)}$ is the industry-specific CES price index.

3.2 Technology and Emissions

To the standard framework above, I add a CES technology that can take multiple fuels $\{q_f\}_{f \in \mathbb{F}}$ indexed by f as inputs to form a fuel composite index F. To avoid notational clutter, I will do the exposition for a single industry and remove the j subscript.[3] This composite fuel represents the total quantity of energy services received from fuel combustion, a process that also emits greenhouse gases into the atmosphere. This technology is similar to the aggregate production function in Hassler, Olovsson and Reiter (2019), who study multiple energy sources in an integrated assessment model of climate change. Fuels have varying degrees of emission intensity, and plants can substitute between them at a rate $\sigma > 0$. Consistent with recent literature on fuel substitution and plant-level fuel consumption patterns, I allow plants to have different fuel sets, indexed by $\mathcal{F} \subseteq \mathbb{F}$ (Murray Leclair, 2024; Kaartinen and Prane, 2024). For instance, one fuel set could include oil and coal, while another could include oil, coal, and natural gas.

In addition to fuel sets, plants are heterogeneous in multiple dimensions of productivity. Plants differ in their hicks-neutral productivity A_i and their fuel-specific productivity, λ_{fi}, where $\sum_{f \in \mathcal{F}} \lambda_{fi} = 1$. The latter allows for flexible patterns of relative fuel consumption across plants. The production function of a given plant is show in equation 2.[4]

[3]This is without loss of generality.

[4]While this framework abstracts from non-fuel inputs, in Appendix A.6.1, I extend everything discussed in this paper to a log-separable production function that takes other unobserved inputs in addition to the fuel composite F_j.

$$Y_i = A_i \underbrace{\left(\sum_{f \in \mathcal{F}_i} \lambda_{fi} \times q_{fi}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}}_{F_i}. \tag{2}$$

Let γ_f be the emission factor that maps one unit of fuel f to tons of carbon dioxide equivalent (CO_{2e}), which is the standard accounting measure for GHG emissions using the Global Warming Potential (GWP) method (U.S. Environmental Protection Agency, 2025). Firm-level emission is the sum of all fuels consumed times their emission factor, which I decompose into the product of emission intensity and output quantity:

$$\begin{aligned} GHG_i = \sum_{f \in \mathcal{F}} \gamma_f \times q_{if} \equiv E_i &= \frac{E_i}{Y_i} \times Y_i \\ &= \underbrace{e_i}_{\text{emission intensity (process factor)}} \times \underbrace{Y_i}_{\text{output quantity (scale factor)}}. \end{aligned}$$

It is useful to compare my technology to the canonical technological framework for pollution in the literature (Shapiro and Walker, 2018; Levinson and Taylor, 2008; Copeland and Taylor, 2004). I define pollution through a composite fuel F, the CES aggregator of multiple fossil fuels. By contrast, canonical models define an implicit pollution function:

$$\text{My model: } Y_i = A_i F_i$$

$$\text{Canonical model: } Y_i = (A_i l_i)^{1-\alpha}(z_i)^{\alpha}$$

In the canonical model, l is labor, and z is total pollution such that one unit of z always pollutes the same amount. However, plants can have varying emission intensity through investments in pollution abatement technologies, making pollution less intensive relative to labor (lower α). By contrast, I define pollution abatement endogenously through fuel substitution. One unit of F can emit different levels of GHG emissions depending on the underlying bundle of fuels that compose it, and that will create variation in emission intensity. Having a specification that maps variation in energy intensity to fuel substitution is desirable in the context of greenhouse gas emissions, where most plant-level emissions reduction comes from substituting cleaner fuels for dirty fuels rather than the end-of-pipe abatement.[5]. Moreover, I can exploit the mapping between the inputs (fossil fuels) and emissions to study emissions reduction efforts.

This technology also has another important implication. By introducing fuel-specific productivity terms λ_{fi}, plants face different realized energy prices when considering the energy service received per dollar spent. I call these prices "effective prices", even though underlying fuel prices in units of fuel quantity (heating potential) per dollar may be the same. This heterogeneity in effective prices implies that a plant with higher relative efficiency in a specific fuel perceives it as cheaper than other fuels because it can use it better. I motivate heterogeneous fuels-specific technology by the empirical fact that different plants (both within and across industries) purchase very different relative fuel quantities even though they often face the same fuel prices.

$$\textbf{Observed}: p_f \quad \longrightarrow \quad \textbf{Effective}: \tilde{p}_{fi} \equiv p_f / \lambda_{fi}$$

Moreover, due to the constant returns assumption, individual effective fuel prices can be aggregated into an effective fuel price index $\tilde{p}_i(F)$ that buys quantities of the composite fuel index F, which is akin to labor as a single input in Melitz (2003a).[6] A constant returns fuel production function enables the analysis of plants' scale decisions separate from the analysis of relative fuel choices. These features have important theoretical implications and will greatly simplify the model estimation.

$$p_i(F) = \left(\sum_{f \in \mathcal{F}_i} \lambda_{fi}^{\sigma} \times p_{fi}^{1-\sigma} \right)^{1/(1-\sigma)} \tag{3}$$

Asymmetric carbon tax

I now introduce the main object of analysis to this framework: a carbon tax that affects a fraction

[5] There are GHG emissions abatement methods that are independent of fuel choices, including carbon capture and storage (CCS) at point source. However, unlike scrubbers for local air pollution, those technologies are not widely adopted because of large infrastructure costs (International Energy Agency, 2024). Moreover, the B.C. and Quebec carbon taxes did not incentivize plants to invest in such end-of-pipe abatement because the tax was levied on fossil fuel purchase (Government of British Columbia, 2025)

[6] I assume constant returns to scale in the production of the fuel composite. However, this does not require constant returns in other inputs such as labor, capital, and intermediate materials. Other inputs can be nested into another production function that takes the fuel composite along with labor, capital, and intermediate materials as inputs. This approach is common in the fuel substitution literature (Atkinson and Luo, 2023; Hyland and Haller, 2018; Wang and Lin, 2017; Ma et al., 2008; Cho et al., 2004; Pindyck, 1979). In Appendix A.6, I extend my model and all quantitative exercises to account for unobserved inputs. I find no noticeable differences in results.

N_r of plants within each industry. Regulated plants are indexed by $s = r$ and face an additional per-unit tax rate $\{\tau_f\}_{f \in \mathbb{F}}$ which is added to gross fuel prices $p_{fr} = p_f + \tau_f \; \forall f$. In contrast, I index the remaining fraction N_u of unregulated plants by status $s = u$, which face the same gross fuel price as before. Since this is a carbon tax, the fuel-specific tax rate is weakly increasing in fuel pollution intensity:

$$\gamma_\ell \geq \gamma_f \rightarrow \tau_\ell \geq \tau_f \; \forall f \neq \ell$$

The rationale behind this framework is that implementing a uniform tax rate on GHG emissions is typically achieved with a different tax rate across fuels due to varying fuel emission intensity γ_ℓ. For example, coal combustion emits, on average, twice as much CO_{2e} in the air as natural gas, and its tax rate is twice as high. B.C. and Quebec introduced carbon taxes using such per-unit taxes on fossil fuels (Government of British Columbia, 2025; Government of Quebec, 2024).

3.3 Firms' Optimal Decisions

Marginal costs are constant, and I can solve plants' problems in two parts, which correspond to the scale factor and the process factor of GHG emissions. The assumption that the fuel composite F features constant returns to scale in all fossil fuels allows me to quantify the model using pollution release data only.[7] First, I solve the profit-maximizing amount of output quantity Y_{is} that a plant in regulation regime s wants to produce from purchasing the composite fuel good F_{is}, taking as given the effective energy price index inclusive of the tax, $p_{is}(F)$. From this, I can know the equilibrium output quantity and output price P_{is}, which will show up in the *scale factor* of GHG emission. In the second part, I can solve the cost-minimizing bundle of fuels that will form F_{is}. Doing so, I map relative fuel shares to plant-level emissions intensity, which contribute to the *process factor* of GHG emission.

3.3.1 Output Quantity and Price

Plants compete over quantity and face an inverse demand derived from Equations 1. Then, taking as given industry aggregates P and Y, a plant with productivity A in regulation status s solves:

[7] Note that I do not need to impose constant returns to scale of output in all inputs. See Appendix A.6.

$$\max_{Y_{is}} \left\{ P_s(Y_{is}) Y_{is} - c_{si} Y \right\}$$
$$\text{s.t. } P_s(Y_{is}) = \left(\frac{Y_{is}}{\beta C} \right)^{-1/\rho} P^{(\rho-1)/\rho}$$

Since $F_{is} \equiv \frac{Y_{is}}{A_i}$, each plant's marginal cost is the ratio of the input price index to productivity: $c_{is} = \frac{p_{is}(F)}{A_i}$. This marginal cost leads to a standard monopolistic competition equilibrium pricing equation of a constant markup over marginal costs:

$$P_{is} = \frac{\rho}{\rho - 1} \frac{p_{is}(F)}{A_i} \tag{4}$$

3.3.2 Aggregation and Total Fuel Consumption

This individual pricing equation can be aggregated into an industry price index as in Melitz (2003a). I do not make any assumption about the distribution of productivity across plants. It can be completely unrestricted. However, consistent with discussions in Section 2, I am abstracting away from entry and exit. The aggregate price index has the same structure as plant-level output prices, where aggregate marginal cost is a combination of regulated and unregulated input prices weighted by the respective mass of plants in each status over aggregate productivity:

$$P = \frac{\rho}{\rho - 1} \left(\sum_s N_s \int \left(\frac{p_{is}(F)}{A_i} \right)^{1-\rho} di \right)^{1/(1-\rho)} \tag{5}$$

Putting everything together, I can now find the quantity of composite fuel purchased by each plant:

$$F_{is} = \left(\frac{\rho - 1}{\rho} \right)^{\rho} \beta C \frac{P^{\rho - 1}}{p_{is}(F)^{\rho}} A_i^{\rho - 1} \tag{6}$$

The amount of composite fuel a plant demands decreases with the effective fuel price index $\tilde{p}_{is}(F)$ and increases with productivity. Most importantly, it increases with the aggregate price index P, due to a competitive effect that enables plants with relatively lower unit costs to capture a larger share of demand. When a carbon tax raises unit costs in regulated regions, it also drives up the aggregate price index P for all plants. Plants in unregulated regions benefit from this higher P in proportion to the elasticity of demand, but also face drawbacks if consumers substitute away from their industry. However, as long as varieties are gross substitutes ($\rho > 1$), the net impact is a positive reallocation towards unregulated plants. This mechanism serves as the primary channel for carbon leakage in this paper.

3.3.3 Relative Fuel Share

To chose the cost-minimizing share of each fuel that composes F_{is}, plants face the technology defined in equation 2, and their relative fuel choice will only be a function of the interior parameters of the technology, namely interfuel substitutability σ and fuel efficiencies λ_{fi}. Productivity will not matter for relative fuel quantities because it augments the composite fuel index rather than specific fuels. Moreover, I assume that plants take input prices as given and cannot affect such prices with their decisions because they are too small relative to the population of firms that make up global fuel demand. Additionally, supply-side shocks such as new technologies (e.g., fracking) and geopolitical events that shift fuel supply in specific regions often drive fuel price variation. Therefore, taking input prices, fuel set, and F as given, a plant in regulation status s solves the following:

$$\min_{\{q_{fis}\}_{f\in\mathcal{F}_i}} \left\{ \sum_{f\in\mathcal{F}_i} (p_f + \tau_{fs}) q_{fis} \right\} \text{ s.t. } F = \left(\sum_{f\in\mathcal{F}_i} \lambda_{fis} \times q_{fis}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)} \tag{7}$$

The solution to this problem gives rise to plant-specific effective fuel prices and energy price indices. Conditional on fuel productivity, this perceived price index is higher for regulated plants because $p_{fr} = p_f + \tau_{fr}$ while $p_{fu} = p_f$ assuming that fuels are gross substitutes ($\sigma > 1$). I define the share of fuel f that makes up the composite fuel F as a simple function of effective input prices. As the effective price of a fuel increases, the relative quantity of that fuel decreases at a rate σ due to substitution towards other fuels.

$$q_{fis}(F) = \left(\frac{\tilde{p}_{fis}}{p_{is}(F)} \right)^{-\sigma} F \tag{8}$$

3.3.4 Emission Intensity

Emission intensity is the amount of GHG emissions as a fraction of output that a plant produces and can be endogenously determined by the conditional input demand of each fuel times its emission factor γ_f over the plant's output quantity:

$$
\begin{aligned}
e_{is} &= \frac{\sum_{f\in\mathcal{F}_i}\gamma_f \times q_{fis}}{Y_{is}} \\
&= \frac{1}{A_i}\sum_{f\in\mathcal{F}_i}\gamma_f\left(\frac{\tilde{p}_{fis}}{p_{is}(F)}\right)^{-\sigma}
\end{aligned}
$$

As in Shapiro and Walker (2018), emission intensity is locally decreasing in productivity. Moreover, while there is no capital and labor in the technology, if a plant is highly intensive in capital and/or labor relative to fuel, this model will capture this as a higher productivity (less fuel required to produce a unit of output), hence lower emission intensity, which is precisely what would happen if capital and labor were in the model.[8]

When a plant gets regulated, it faces higher prices for dirtier fuels relative to cleaner ones. Due to possible substitution, plants will change their optimal combination of fuels that make up $\mathcal{F}_i$. This reallocation shifts fuel use towards fuels with lower emission factors, reducing emission intensity. These changes do not induce carbon leakage: unregulated plants still face the same gross fuel prices as before and choose the same optimal bundle. Formally, for each fuel k, there exists a threshold emission intensity γ_k^* such that when a fuel's emission factor exceeds this threshold ($\gamma_k > \gamma_k^*$), an increase in its price lowers the plant's emission intensity: $\frac{\partial e_{is}}{\partial p_k}\Big|_{\gamma_k>\gamma_{ki}^*} < 0$. Conversely, if a fuel's emission factor falls below the threshold ($\gamma_k < \gamma_k^*$), raising its price increases the plant's emission intensity.

$$
\gamma_{ki}^* = p_k\frac{\sum_{f\neq k}\gamma_f(\lambda_{fi}/p_f)^{-\sigma}}{\sum_{f\neq k}p_f^{\sigma-1}\lambda_{fi}^{\sigma}} \tag{9}
$$

An increase in the relative price of fuels that pollute above γ_{ki}^* will lead to substitution towards less polluting fuels and a decrease in emission intensity, which happens when plants face a carbon tax.

[8] For this to be valid, however, I assume that fuel taxes/prices do not affect the price of unobserved inputs like capital and labor. I discuss this in more detail in Appendix A.6.

3.4 Counterfactual Outcomes—Emissions, Output and Profits

Now that I have characterized the production structure in this economy, I can define the optimal level of GHG emissions for each plant, which is, by definition, the product of output quantity and emission intensity:

$$
\begin{aligned}
GHG_{is} &= Y_{is}/A_i \times e_{is}A_i \\
&= \underbrace{\left(\frac{\rho-1}{\rho}\right)^{\rho}\beta C\frac{P^{\rho-1}}{\tilde{p}_{is}(F)^{\rho}}A_i^{\rho-1}}_{\text{scale factor}} \times \underbrace{\sum_{f\in\mathcal{F}_i}\gamma_f\left(\frac{p_{fs}/\lambda_{fis}}{\tilde{p}_{is}(F)}\right)^{-\sigma}}_{\text{process factor}}
\end{aligned}
$$

Two key factors determine GHG emissions. The first is the scale factor, which depends on macro parameters and the relative perceived fuel price indices across regions. Plants facing a relatively lower fuel price index produce more and, as a result, emit more. The same logic applies to productivity A_i: more productive plants generate higher output and thus higher emissions. The second factor is the process factor, which reflects the relative differences in "effective" prices among the fuels that comprise the fuel price index. We can apply exact hat algebra to understand how GHG emissions change after a carbon tax. Let GHG' denote counterfactual emissions in the absence of the tax. In Equation 10, I am comparing emissions with the tax relative to counterfactual emissions without the tax:

$$
\underbrace{\frac{GHG_{is}}{GHG'_{is}} = \left(\frac{P}{P'}\right)^{-1}}_{\text{scale (aggregate output)}} \times \underbrace{\left(\frac{p_{is}(F)/P}{p'_{is}(F)/P'}\right)^{-\rho}}_{\text{composition (outpout reallocation)}} \times \underbrace{\frac{\sum_{f\in\mathcal{F}_i}\gamma_f(\lambda_{fi}/p_{fs})^{\sigma}}{\sum_{f\in\mathcal{F}_i}\gamma_f(\lambda_{fi}/p'_{fs})^{\sigma}}\left(\frac{p_{is}(F)}{p'_{is}(F)}\right)^{\sigma}}_{\text{process factor}} \tag{10}
$$

There are three noteworthy terms. First, a scale factor reduces emissions due to a reduction in aggregate output in the economy, captured by the overall increase in marginal cost from the carbon tax, pushing down aggregate demand. Second, a composition factor reflects emissions adjustments due to output reallocating from regulated to unregulated plants. Regulated plants' input cost relative to the average input cost in the economy is larger under the carbon tax $\frac{p_{ir}(F)/P}{p'_{ir}(F)/P'} > 0$. These plants become relatively less competitive and output reallocates to unregulated plants', whose input cost is relatively lower under the carbon tax $\frac{p_{iu}(F)/P}{p'_{iu}(F)/P'} = \frac{P'}{P} < 0$. Output also reallocates among regulated plants because they have heterogeneous fuel technologies and fuel sets, leading to different changes in fuel price indices. Plants with technologies that favor cleaner fuels face lower marginal abatement costs ex-ante, leading to smaller input cost increases, allowing them to remain more competitive.

Output reallocation is the primary channel for carbon leakage. As long as output varieties are gross substitutes ($\rho > 1$), the composition channel dominates the scale channel for unregulated plants, leading to a net increase in carbon leakage. Third, a process factor reduces regulated plants' emissions through inter-fuel substitution because the carbon tax causes an increase in the price of dirty relative to cleaner fuels.

In the next section, I use publicly available pollutant release data from Canadian manufacturing plants to identify plant-level counterfactual emissions, output, and profits. This data allows me to quantify the direct impacts of the policy on regulated plants and the indirect impacts on emissions leakage and output reallocation towards unregulated plants.

4 Data and Regulatory Details

The empirical application of this model is a study of the British Columbia and Quebec carbon taxes. I am initially considering three main fuel types: Natural Gas, Oil, and Coal. Since this is a closed-economy model, I only look at competition between Canadian manufacturing plants.

4.1 Pollution and fuel data

The primary dataset used for plant-level pollution is the National Pollutant Inventory Release (NPRI), which records each pollutant emitted by most Canadian plants since 2000 from stationary combustion (Environment and Climate Change Canada, 2025). This dataset records 280 pollutants, but I only look at 8 of the most relevant pollutants to separately identify coal, oil, and natural gas. I get between 700 and 900 plants annually between 2002 and 2015.[9] To recover plant-level fuel quantities in comparable units, I invert each fuel's chemical reaction under standard stationary combustion practices, whose details is available from the following reports: "AP-42: Compilation of Air Emissions Factors from Stationary Sources" (U.S. Environmental Protection Agency, 2024a).[10] Thus, I get eight equations (pollutants) with three unknowns (fuels) that I solve by least squares

[9] I choose this time frame because most plants did not report to the NPRI before 2002 and because many other Canadian provinces introduced carbon taxes and other environmental regulations in 2016.

[10] There can be heterogeneity in the quantity of each pollutant released by each fuel primarily due to combustion efficiency. However, heterogeneity in chemical reactions is much larger across fuel types than within. For example, the chemical reaction from anthracite and sub-bituminous coal is much more similar to that of natural gas combustion.

minimization subject to a non-negativity constraint. I do this procedure for each plant and each year. I remove ≈ 20% of plants for which I cannot identify different fuel types separately because those plants report less than three pollutants.

$$\Theta_{p,it} = \sum_{f \in \mathcal{F}_{it}} \delta_{pf} \cdot q_{fit}, \quad \forall p \in \mathcal{P}$$

Table 1 compiles information provided by the U.S. Environmental Protection Agency (EPA) on the mapping between one mmBtu of each fuel and quantities of each pollutant (in pounds) released into the atmosphere. In Appendix A.3.2, I show a version covering a much wider range of pollutants available both in the EPA AP-42 report and the NPRI data. It includes all the organic compounds that form total and volatile organic compounds and all speciated metals. However, the performance of this approach remains virtually identical to the main version.

Pollutant	**Element**	**Coal**	**Natural Gas**	**Oil**
Carbon monoxide	CO	2.00×10^{-2}	1.20×10^{-1}	3.51×10^{-2}
Nitrogen oxides	NOx	4.63×10^{-1}	7.31×10^{-2}	2.38×10^{-1}
Lead	Pb	2.08×10^{-4}	4.87×10^{-7}	1.06×10^{-5}
PM10	PM10	3.51×10^{-1}	7.41×10^{-3}	2.19×10^{-2}
PM2.5	PM2.5	1.62×10^{0}	7.41×10^{-3}	5.96×10^{-2}
Sulphur dioxides	SO2	1.48×10^{0}	5.85×10^{-4}	1.07×10^{0}
Total Particulate Matter	TPM	8.49×10^{-1}	7.41×10^{-3}	4.13×10^{-2}
Volatile organic compounds	VOC	5.94×10^{-3}	5.36×10^{-3}	4.21×10^{-3}

Table 1: Comparison of emission factors from natural gas, oil, and coal combustion (lb/mmBtu)

Source: AP-42: Compilation of Air Emissions Factors from Stationary Sources (U.S. Environmental Protection Agency, 2024a). This table is constructed by averaging different measures of stationary emissions from the EPA's Compilation of Stationary Emission Factors (AP-42). I look at oil typically used for stationary combustion: distillate (No. 1, 2, 4) and residual fuel oils (No. 5,6). I abstract away from gasoline, diesel, and similar fuels related to transportation because the NPRI data captures air emissions from stationary combustion. Natural gas is a more homogeneous fuel than coal and oil. The emissions factors for coal are created by averaging emissions for different coal grades (anthracite, bituminous, sub-bituminous, and lignite). Similarly, the emissions factors for oil are the average emission factors for different types of fuel oils used in manufacturing, referring to different types of distillate and residual oils. *Million British Thermal Units* (mmBtu) is a standard measure of heating potential for comparing different fuels.

To validate this procedure, I compare estimated fuel shares to aggregate shares reported in official statistics (Figure 2). I also cross-checked the method using plant-level data from the U.S. Greenhouse Gas Reporting Program (GHGRP) (U.S. Environmental Protection Agency, 2024b). The estimates closely match oil shares but tend to underestimate coal relative to natural gas. However, coal accounts for only 3–6% of total fuel use, reflecting its phaseout in Canadian manufacturing. In addition, several provinces impose coal regulations. For these reasons, I exclude coal from the analysis. Figure 9 in the Appendix further validates the procedure by comparing estimated and official fuel shares by industry. I exclude three industries: Wood, fabricated metal, and transportation equipment. These industries have a small number of observations and imprecise fuel share estimates.

4.1.1 Greenhouse Gases

Lastly, pollutants reported by the NPRI are not greenhouse gases contributing to global climate change (e.g., carbon dioxide CO_2, methane CH_4, and nitrous oxide N_2O). Once I observe fuel quantities, I use another conversion table from the EPA that maps fuel quantities to greenhouse gases. Using the GHG emission factors from Table 1, I then create a single measure of carbon dioxide equivalent (CO_{2e}) using the global warming potential (GWP) method (U.S. Environmental Protection Agency, 2025). In principle, I can extend this procedure to study fuel usage by geolocated plants from remote sensing data, which may be interesting in regions lacking the regulatory body necessary to compile a dataset such as the NPRI, enabling the study of cross-country carbon leakage.

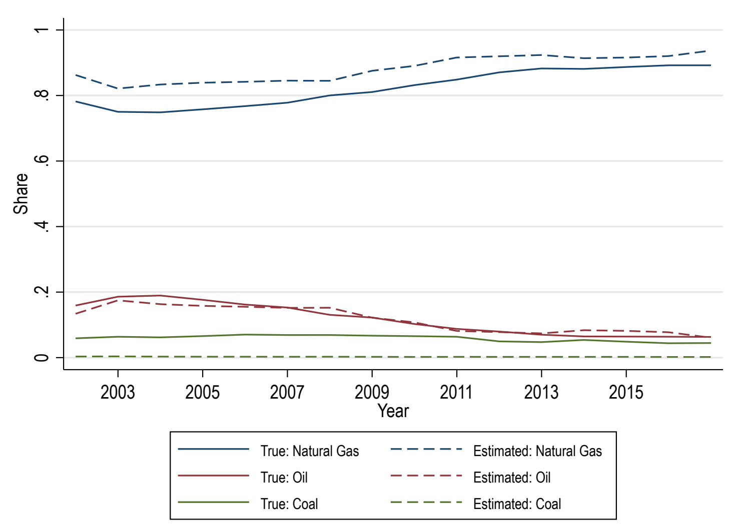


Figure 2: Aggregate fuel shares over time — true vs. estimates

Notes: This figure is constructed by averaging relative fuel shares over time. Solid lines reflect estimates, whereas blue lines reflect true fuel shares. I get true fuel shares from Statcan Table 25-10-0025-01 (formerly CANSIM 128-0006), which records annual energy consumption by fuel across manufacturing industries from the Annual Industrial Consumption of Energy Survey (ICE) (Statistics Canada, 2024). I use linear interpolation for missing values.

	Carbon dioxide kg CO_2/mmBtu	Methane g CH_4/mmBtu	Nitrous Oxide g N_2O/mmBtu	Carbon dioxide equivalent kg CO_{2e}/mmBtu (100-Year GWP)
Coal	98.2	11	1.6	98.9
Oil	70.5	3	0.6	70.7
Natural Gas	56.1	1	0.1	56.2

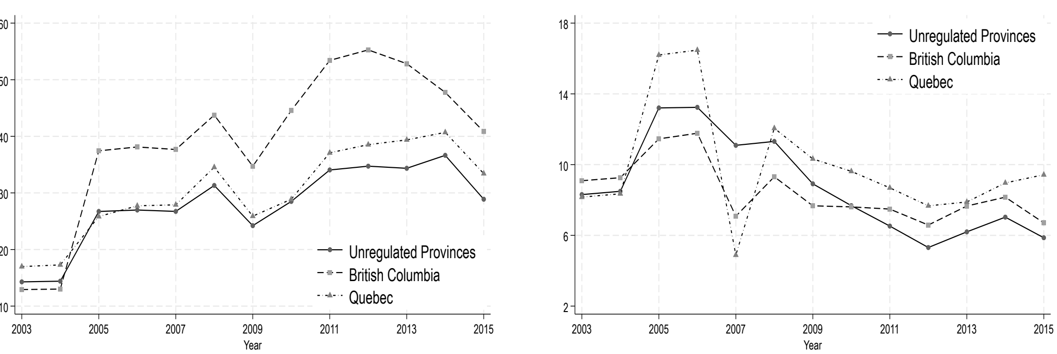
Table 2: GHG Emission Factors

Source: GHG Emission Factors Hub (U.S. Environmental Protection Agency, 2025). Notes: I use the standard 100-year Global Warming Potential method (GWP) to convert methane and nitrous oxide emissions into carbon dioxide equivalent. Emission factors get updated annually by the U.S. EPA. The last column is the final measure of GHG emissions.

4.2 Other Data

4.2.1 Fuel Prices

I find province-specific prices paid by industrial consumers in CAD/GJ from the Canadian Energy Regulator (Canada Energy Regulator, 2023) for both natural gas and oil. These prices vary by province but exclude all taxes. The Canadian government levies a 5% goods and service tax (GST) and provinces have different ad-valorem sales taxes (PST/HST) on furnace oil and natural gas (Canada Revenue Agency, 2022).[11] I manually add provincial and federal taxes levied on both fuels and convert prices in real CAD/mmbtu (base year 2019). Figure 3 shows fuel prices across regions.



(a) Oil

(b) Natural gas

Figure 3: Fuel prices (real CAD/mmBtu) — excluding carbon tax

Notes: These prices reflect the annual average industrial end-use price paid for each fuel, including all standard taxes (GST/HST), but excluding the carbon tax.

[11] Excluding carbon taxes, the Canadian federal government and provincial governments do not levy excise taxes for furnace oil and natural gas. Fuel excise taxes are only imposed on gasoline, diesel, and propane (for motor vehicles), which are not included in this paper because we are looking at fuel usage from stationary combustion.

4.2.2 Carbon Taxes

British Columbia implemented a revenue-neutral, province-wide carbon tax in July 2008 that started at $\$10/tCO_{2e}$ and increased by CA $5/t$ each July to CA $35/t$ by 2013, remaining frozen at that level through 2016 (Government of British Columbia, 2008; Pembina Institute, 2014; Government of British Columbia, 2025). The tax was levied on nearly all fossil fuels, covering roughly 70% of the province's greenhouse-gas emissions. Quebec imposed a modest carbon tax of about $\$3.50/tCO_{2e}$ in 2007 that remained constant until 2015 (Torys LLP, 2007). The tax was levied on fossil fuels and thus targeted all plants. Both of these regulations are the primary policies analyzed in this paper.

Two additional policies are worth mentioning. In 2013, Quebec introduced a cap-and-trade system which targeted large plants emitting more than 25,000 metric tons of CO_{2e}). In 2014, Quebec linked its system to California's as part of the Western Climate Initiative (WCI), a collaboration of independent jurisdictions working on emissions trading policies (Government of Quebec, 2024). Alberta also had a carbon pricing mechanism every year between 2007 and 2015, which targeted large industrial plants emitting more than 100,000 metric tons of CO_{2e}. Plants had to choose between improving emissions intensity by 12%, paying a price of $\$15/tCO_{2e}$ for emissions above the plant's threshold, or, equivalently, buying offset credits (Alberta Environment, 2009).[12]

I exclude these two regulations because they do not easily map to per-unit fossil fuel price increases. However, in Appendix A.7, I repeat the entire analysis after removing large plants covered by Alberta's carbon policy and Quebec's cap-and-trade system. The results remain largely unchanged. No other province or territory had implemented a carbon tax or cap-and-trade system before the end of 2016. In October 2016, the Trudeau government announced a Pan-Canadian approach to carbon pricing, requiring all jurisdictions to meet a national benchmark starting in 2018. This policy lies outside the scope of the paper.

To construct fuel-specific carbon tax rates, I map one mmBtu of each fuel in tons of CO_{2e} equivalent using γ_f, which is calculated in Table 2, and I multiply this by the level of the carbon tax. Table 3 reports carbon taxes levied on each fuel.

[12] Because Alberta's regulation was intensity-based, only the fraction of emissions above each plant's benchmark was priced. One study finds that the effective cost of the policy was only $\$1.8/tCO_{2e}$ for targeted plants (Read, 2014).

	British Columbia						Quebec
	2008	2009	2010	2011	2012	2013-2015	2008-2015
Natural Gas (\$/mmBtu)	0.53	0.8	1.06	1.33	1.59	1.86	0.19
Oil (\$/mmBtu)	0.72	1.08	1.43	1.79	2.15	2.51	0.25
Coal (\$/mmBtu)	0.99	1.48	1.98	2.47	2.97	3.44	0.35
CO_{2e} (\$/ton)	10	15	20	25	30	35	3.5

Table 3: Carbon Tax Rates Until 2015

Sources: B.C.: Government of British Columbia (2025, 2008); Pembina Institute (2014), Quebec: Torys LLP (2007).

4.2.3 Aggregate data

To get aggregate consumption over time, C_t, I use the share of Canadian nominal GDP from manufacturing. Then, I can get β_{jt}, the shares of Canadian manufacturing GDP that come from each 3-digit NAICS manufacturing industry (Statistics Canada, 2025a). Since GDP is in dollar amount, this is going to be the share of manufacturing consumption associated with each industry: $\beta_{jt} = \frac{Y_{jt}P_{jt}}{C_j}$. Through period-by-period variation in C_t and β_{jt}, I allow for industry-specific demand shocks. To see this, if there is a one-time positive demand shock to industry j, this will increase aggregate demand C_t while simultaneously increasing β_{jt} and decreasing β_{kt} $\forall k \neq j$ such that the amount of consumption going to all other industries remains unchanged and $\sum_j \beta_{jt} = 1$ is still satisfied. Additionally, since there is only one big market in the model, a region-specific demand shock would effectively affect all plants regardless of location. Variation in C_t without changing relative industry shares reflects such a demand shock.

5 Identification and Estimation

I propose a credible identification strategy that explicitly leverages variation in the carbon tax to identify all relevant structural parameters. Since the empirical application of this model is the B.C. and Quebec carbon taxes, I am only considering the universe of Canadian manufacturing plants under the plausible assumption that those plants take input prices as given and cannot affect global input prices with their individual decisions. As such, there will be no variation in aggregate fuel demand induced by carbon regulation that would affect equilibrium fuel prices in general equilibrium, commonly referred to as the fossil-fuel channel of carbon leakage in the literature (Fowlie and Reguant, 2018). Following the literature on estimating CES functions, I normalize the production function around the geometric mean of each variable (Grieco et al., 2016; León-Ledesma et al., 2010). For a given plant in year t, the production function becomes

$$\frac{Y_{it}}{\overline{Y}} = A_{it}\left(\sum_{f\in\mathcal{F}_{it}} \lambda_{fit}\left(\frac{q_{fit}}{\overline{q}_f}\right)^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}.$$

There are two sets of parameters in the model. First, some parameters relate to the production technology, such as baseline fuel shares, the interfuel substitution elasticity: $\left\{\{\lambda_{fit}\}_{f\in\mathbb{F}}\right\}_{i,t}, \sigma\}$. Other parameters such as the elasticity of demand ρ relate to plant-level output decisions (macro parameters). Ideally, if I had data on plant-level output and emission intensity, I could separately identify both sets of parameters like Shapiro and Walker (2018), Ganapati et al. (2020), and Aichele and Felbermayr (2015) since technology parameters only appear in emission intensity and other parameters only appear in plant-level output.

However, I only observe plant-level pollutants released along with aggregate industry statistics. An important contribution of this paper is to show identification of the direct and leakage effects of a carbon tax on emissions under these flexible data requirements. Importantly, I do not impose that fuels and output varieties are gross substitutes ($\sigma > 1, \rho > 1$), allowing to reject the carbon leakage hypothesis—recalling from Section 3.4 that carbon leakage is only possible if output varieties are gross substitutes. To do this, I separate the estimation into two stages.

The first stage maps changes in the *relative* carbon tax between different fuels to changes in *relative* quantity of fuels consumed by each plant to identify technology and interfuel substitution parameters in closed-form. The key to this step is that the standard treatment and control dichotomy goes through because the tax does not impact unregulated firms' relative fuel quantities. Thus, I can rely on the Stable Unit Treatment Value Assumption (SUTVA).

In the second stage, I use estimates from the first stage to map changes in the level of the carbon tax across fuels to changes in the common scale component of fuel consumption. This scale component reflects plant productivity and industry aggregates, which I use to identify the elasticity of demand. I now reintroduce the industry subscript j and year subscript t into the model.[13]

[13] When possible, I use the plant subscript i, which absorbs the industry j and province s subscripts.

$$\text{Individual fuel quantities: } q_{fit} = \left(\frac{p_{fst} + \tau_{fst}}{p_{it}(F)}\right)^{-\sigma} F_{it}$$

$$\text{Composite fuel (scale): } F_{it} = \left(\frac{\rho - 1}{\rho}\right)^{\rho} \beta_{jt} C_t \frac{P_{jt}^{\rho-1}}{p_{it}(F)^{\rho}} A_{it}^{\rho-1}$$

Intuitively, I am leveraging two different types of variation at both estimation stages. The elasticity of substitution is identified from variation in the *relative* tax rate between two natural gas and oil, which increases the price of using dirtier fuels relative to cleaner ones. On the other hand, the elasticity of demand is identified from variation in the *scale* of the carbon tax across all fuels. The scale of the carbon tax identifies the curvature of demand because it's a cost-shifter that increases the marginal cost of production net of fuel substitution.

5.1 Stage 1: Identification of technology parameters

I use relative first-order conditions from the cost-minimization problem in Equation 7 to get an estimating equation in (log) relative fuel quantities for oil (o) and natural gas (g):

$$\ln(q_{oit}/\overline{q}_o) - \ln(q_{git}/\overline{q}_g) = \sigma(\ln p_{gst} - \ln p_{ost}) + \sigma(\ln \lambda_{oit} - \ln \lambda_{git}) + \sigma \ln(\overline{q}_g/\overline{q}_o)$$

Some variation in fuel prices may correlate with unobserved fuel-specific technological change $(\ln \lambda_{oit} - \ln \lambda_{git})$, which would bias the estimate of the elasticity of substitution σ. To address this concern, I explicitly leverage variation in the carbon tax to identify σ. There are two underlying identifying assumptions. First, I assume the carbon tax did not cause systematic changes in fuel-specific technology for treated plants. I motivate this assumption by Figures 2 and 9, indicating that technology was already favoring natural gas before the tax, the cleanest fossil fuel. Moreover, I capture industry-wide clean technology development with industry-by-year fixed effects, which affects regulated and unregulated provinces. Second, I assume that relative fuel quantities would have trended parallel in regulated and unregulated provinces, after conditioning on a set of fixed effects that capture industry-specific trends and permanent differences across plants in fuel-specific technology.

To test the second identifying assumption, I create a difference-in-difference event study regression

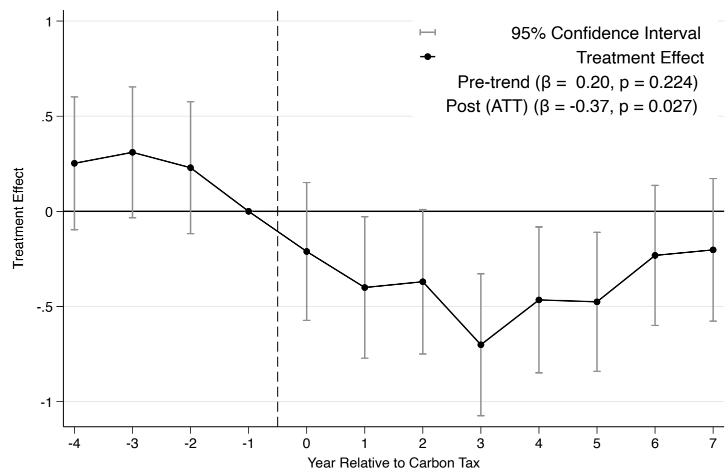


Figure 4: Carbon tax event study — oil relative to natural gas

Notes: This figure reports event study estimates of the carbon tax on regulated plants' share of oil relative to natural gas from a two-way-fixed effects (TFWE) regression. I report the overall effect and pre-trend tests in the legend. The x-axis represents years relative to the first year in which each province implemented the carbon tax.

in which I estimate the average treatment on the treated and investigate pre-trends:

$$\ln(q_{it}^o/\overline{q}^o) - \ln(q_{it}^g/\overline{q}^g) = \alpha_i + \alpha_{jt} + \sum_{k\neq -1} \beta_k D_{st}^k + \epsilon_{it},$$

where D_{st}^k is an indicator for whether plants in province s where treated $t-k$ years relative to the start of the carbon tax. For transparency, I also do the same event study, looking at coal relative to natural gas and coal relative to oil, and report results in Appendix A.4. The carbon tax was not associated with systematic variation in fuel shares relative to coal, which further validates dropping coal from this analysis.

In Figure 4, I find that the carbon tax caused an average decrease of 37% in the share of oil relative to natural gas used by regulated plants, with no sign of pre-trends—the effect disappeared by the end of the sample in 2016, which is not innocuous. Justin Trudeau became prime minister of Canada in 2015 with the key electoral promise of instating a nationwide carbon tax, which took effect in 2018. One could expect that plants started phasing out oil in anticipation of the nationwide carbon tax.

I then construct a reduced-form version of the estimating equation that mimics the event study above. In this setup, I attribute the ATT to variation in the carbon tax. To do this, I instrument variation in relative fuel prices with the relative carbon tax between natural gas and oil. The regression is in log and the carbon tax is often zero, so I use the inverse hyperbolic sine transformation (IHS) to construct my instrument, which is increasingly common in applied econometrics (Aihounton and Henningsen, 2020)[14]:

$$\ln z_{st} \equiv \ln\left(\tau_{st}^{g} + \sqrt{(\tau_{st}^{g})^2 + 1}\right) - \ln\left(\tau_{st}^{o} + \sqrt{(\tau_{st}^{o})^2 + 1}\right) = \text{arcsinh}(\tau_{st}^{g}) - \text{arcsinh}(\tau_{st}^{o})$$

Next, I do one more step to get consistent second-stage estimates of the elasticity of demand using estimates from the first stage (Ryan, 2012; Ellickson and Misra, 2008). I cannot attribute all variation in plant fixed effects to technology variation while consistently estimating the elasticity of demand in the next stage because of the incidental parameter problem. For this reason, I follow the approach of Bonhomme and Manresa (2015) and use K-means clustering to group plant fixed-effects into technology clusters g, which allows for a consistent estimation of technology clusters as $N \to \infty$. I do this in addition to industry-by-year fixed effects and province fixed effects. The estimating equation for the elasticity of substitution then becomes as follows:[15]

$$\begin{aligned}
\ln(q_{it}^{o}/\overline{q}^{o}) - \ln(q_{it}^{g}/\overline{q}^{g}) &= \alpha_0 + \alpha_g + \alpha_s + \alpha_{jt} + \sigma(\ln p_{st}^{g} - \ln p_{st}^{o}) + \epsilon_{it} \\
\ln p_{st}^{g} - \ln p_{st}^{o} &= \gamma_0 + \gamma_g + \gamma_s + \gamma_{jt} + \beta \ln z_{st} + u_{st}
\end{aligned}$$

After estimating the model, I use all fixed effects to recover estimates of plant-specific technological parameters, taking out the normalization term $\hat{\sigma}\ln(\overline{e}^{g}/\overline{e}^{o})$:

[14] I also experimented with alternative log transformations such as $\ln((1+\tau_{st}^{g})/(1+\tau_{st}^{o}))$ and results are extremely similar.

[15] Note that the first stage can be mis-specified, as long as it captures some of the relevant variation. In other words, the functional relationship between fuel prices and the carbon tax need not be exact. see Ganapati et al. (2020) for details. This is important because the carbon tax is a per-unit tax, not an ad-valorem tax, so relative tax rates are not log-separable from relative fuel prices.

	(1) Baseline	(2) Baseline + QC control	(3) BM (2015)	(4) BM (2015) + QC control
Elasticity of Substitution: $\hat{\sigma}$	1.411*	2.004*	1.493**	2.117***
	(0.612)	(0.800)	(0.521)	(0.643)
Industry Year FE	Yes	Yes	Yes	Yes
Quebec Financial Crisis Dummies	No	Yes	No	Yes
Firm FE	Yes	Yes	Clustered	Clustered
Province FE	Absorbed	Absorbed	Yes	Yes
Observations	3,032	3,032	3,032	3,032

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: IV Estimates of Elasticity of Substitution

Notes: This table reports estimates of the elasticity of substitution using the carbon tax as an instrument for relative fuel prices. The number of observations represents the number of plants with both oil and natural gas in their fuel set. The first column is the baseline and refers to the model with plant fixed effects. The second column is the baseline plus 2007 and 2008 dummies for Quebec, which saw a large variation in the price of natural gas relative to other provinces in the midst of the financial crisis. See 3b. Some of this variation conflates with the carbon tax, so I added it as a separate control. The last two columns use the clustering approach of Bonhomme and Manresa (2015) instead of plant fixed effects.

$$\hat{\lambda}_{oit} = \frac{\exp(\hat{\alpha}_g + \hat{\alpha}_s + \hat{\alpha}_{jt})}{\exp(\hat{\alpha}_g + \hat{\alpha}_s + \hat{\alpha}_{jt}) + 1}$$

$$\hat{\lambda}_{git} = \frac{1}{\exp(\hat{\alpha}_g + \hat{\alpha}_s + \hat{\alpha}_{jt}) + 1}$$

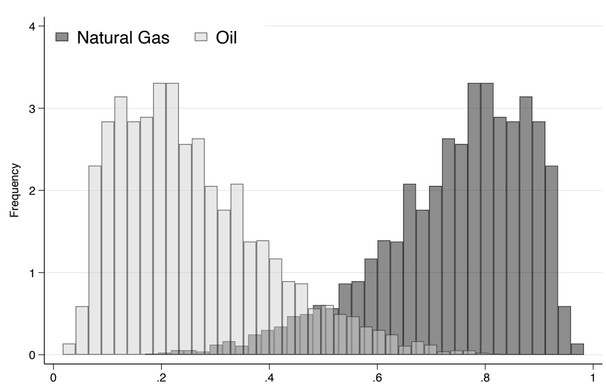


Figure 5: Distribution of technological parameters

Notes: This is the distribution of estimated natural gas and oil technological parameters for plants that are using both oil and natural gas

5.2 Stage 2: Identification of demand parameters

Upon estimating technology parameters, I can use log fuel quantities subtracted from a fuel-specific substitution term to recover the scale component common to all fuels, $\ln F_{it} \equiv \ln q_{fit} + \hat{\sigma}(\ln \hat{p}_{it}(F) - p_{fst}$. Expanding the log fuel composite term naturally leads to a structural and associated reduced-form estimating equation. The latter recovers the elasticity of demand under certain conditions, which I discuss below.

$$\begin{aligned}\ln F_{it} &= \rho \ln \left(\frac{\rho - 1}{\rho}\right) + \ln C_t + \ln \beta_{jt} + (\rho - 1) \ln P_{jt} - \rho \ln \hat{p}_{it}(\mathcal{F}_{it}) + (\rho - 1) \ln A_{it} \\ &= \delta_{jt} - \rho \ln \hat{p}_{it}(\mathcal{F}_{it}) + \epsilon_{it}\end{aligned}$$

First, the CES fuel price index is the primary independent variable. It is very flexible as it can vary across plants and years based on fuel-specific technologies. However, it also implies that variation in this price index may be correlated with variation in unobserved hicks-neutral productivity A_{it}, especially if there are fixed costs of adjusting technology. Hence, OLS would not identify ρ. For this reason, I create another instrument that exploits variation in the *scale* of the carbon tax:

$$\ln \tilde{\tau}_{st} = \text{arcsinh}\Big(\tau_{st}^{f} / \gamma_f\Big) \quad \forall f.$$

By construction, $\tau_{st}^{f} / \gamma_f \equiv \tau_{st}^{co2}$ is the same across all fuels and corresponds to the *level* of the carbon tax.[16] While this energy price index is nonlinear in the carbon tax, the first stage can be misspecified as long as relevance and the exclusion restrictions are satisfied (Ganapati et al., 2020). Intuitively, the elasticity of demand is identified from variation in the *scale* of the carbon tax across all fuels, increasing plants' marginal cost of production net of fuel substitution. The carbon tax thus acts as a cost shifter which identifies the curvature of demand, ρ. The underlying assumption is that the carbon tax was not systematically related to other unobserved variables that affected fuel choices.

Second, the input price index is a generated regressor. Following much of the applied literature on

[16] I also report results with the level of the tax (without any log transformation) as an instrument and with $\ln(1 + \tau_{st}^{co2})$ as an instrument.

two-step estimation with generated regressors, I bootstrap individual plant histories to get confidence intervals for the elasticity of demand ρ that takes into account the variance in the estimated elasticity of substitution $\hat{\sigma}$ (Ryan, 2012; Ellickson and Misra, 2008)). This approach also allows me to get confidence intervals for all counterfactual outcomes.

In practice, I add province fixed effects to control for the fact that, on average, plants in regulated provinces may be more/less productive than plants in unregulated provinces, which would violate the exclusion restriction and bias ρ. I estimate the elasticity of demand with 2SLS by specifying the following reduced-form equation. I show results in Table 5, which are robust to different specifications of the instrument.

$$\ln F_{it} = \delta_{jt} + \delta_s - \rho \ln p_{it}(\mathcal{F}_{it}) + \epsilon_{it}$$
$$\ln p_{it}(\mathcal{F}_{it}) = \gamma_{jt} + \delta_s + \eta \ln \tilde{\tau}_{st} + u_{it}$$

	OLS	IV (level) τ_{st}^{co2}	IV (log) $\ln(1+\tau_{st}^{co2})$	IV (IHS) $\text{arcsinh}(\tau_{st}^{co2})$
Elasticity of demand $\hat{\rho}$	0.613	1.581	1.565	1.580
	(0.122)***	(0.417)***	(0.414)***	(0.417)***
	[0.383]*	[0.954]*	[0.947]*	[0.954]*
Industry Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	8,868	8,868	8,868	8,868

Standard errors in parentheses
Two steps Bootstrap standard errors in brackets
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Elasticity of Demand Estimation

Notes: The standard errors in brackets account for the estimated variance in the elasticity of substitution. The number of observations is larger than in the elasticity of demand regression for two reasons. First, this includes plants that use only oil or only gas. Second, I treat each fuel quantity as a single observation. I use fuel fixed effects to account for cross-fuel correlation within plants.

6 Counterfactuals

I now have everything needed to recover counterfactual outcomes had the carbon tax not been introduced in B.C. and Quebec. In this counterfactual, regulated plants are subject to unregulated fuel prices. Plants in other provinces do not get a competitive edge from the carbon tax. Doing this exercise for regulated and unregulated plants separately will recover the tax's direct and leakage effects. The counterfactual quantities of interest I can recover are GHG emissions, output, and profits. Let Y and Y' denote factual (with tax) and counterfactual (without tax) outcomes, respectively. I can recover factual relative to counterfactual outcomes without observing plant-level productivity using exact hat algebra:[17]

$$\frac{GHG_{it}}{GHG'_{it}} = \left(\frac{P_{jt}}{P'_{jt}}\right)^{\rho-1}\left(\frac{p_{it}(\mathcal{F}_{it})}{p'_{it}(\mathcal{F}_{it})}\right)^{\sigma-\rho}\frac{\sum_{f\in\mathcal{F}_{it}}\gamma_f(\lambda_{fit}/p_{fst})^{\sigma}}{\sum_{f\in\mathcal{F}_{it}}\gamma_f(\lambda_{fit}/p'_{fst})^{\sigma}} \tag{Emissions}$$

$$\frac{Y_{it}}{Y'_{it}} = \left(\frac{P_{jt}}{P'_{jt}}\right)^{\rho-1}\left(\frac{p'_{it}(\mathcal{F}_{it})}{p_{it}(\mathcal{F}_{it})}\right)^{\rho} \tag{Output}$$

$$\frac{\pi_{it}}{\pi'_{it}} = \left(\frac{P_{jt}}{P'_{jt}}\right)^{\rho-1}\left(\frac{p'_{it}(\mathcal{F}_{it})}{p_{it}(\mathcal{F}_{it})}\right)^{\rho-1} \tag{Profits}$$

For each counterfactual outcome, all terms other than relative aggregate price indices $\left(P_{jt}/P'_{jt}\right)^{\rho-1}$ can be recovered directly using estimated parameters. I also need to observe each plant's fuel spending for relative aggregate price indices, which I construct from observed fuel prices and quantities. Let θ_{it} be plant i's total fuel spending relative to other plants in the same industry:

$$\theta_{it} \equiv \underbrace{\frac{\sum_{f\in\mathcal{F}_{it}}(p^f_{st}+\tau^f_{st})e^f_{st}}{\sum_{i\in j}\sum_{f\in\mathcal{F}_{it}}(p^f_{st}+\tau^f_{st})e^f_{st}}}_{\text{Data}} = \underbrace{\frac{(p_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}{\sum_{i\in j}(p_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}}_{\text{Model}}$$

Then, counterfactual aggregate prices can be rewritten as a function of observables only and don't require observing plant-level productivity. The Exact derivations are in Appendix A.5.

$$(\rho-1)\ln(P_{jt}/P'_{jt}) = -\ln\left(\sum_{i\in j}\theta_{it}\left(\frac{p_{it}(\mathcal{F}_{it})}{p'_{it}(\mathcal{F}_{it})}\right)^{1-\rho}\right)$$

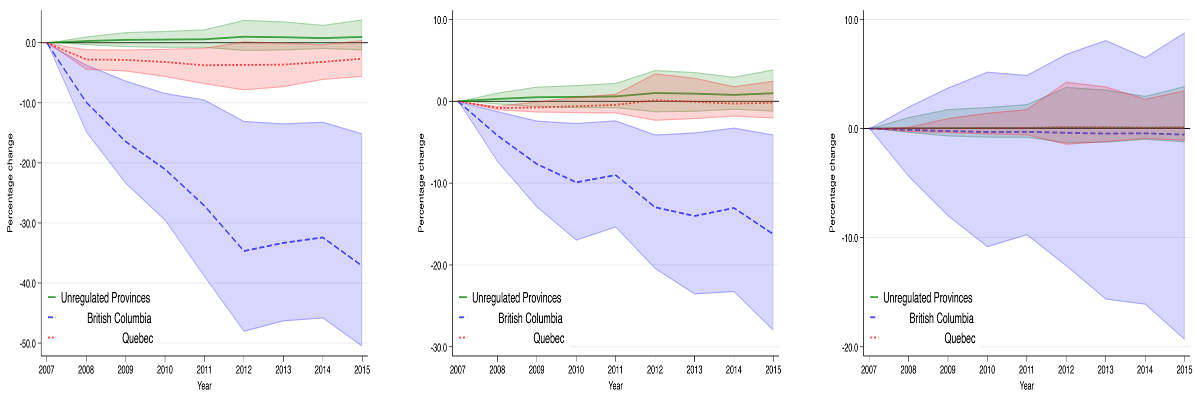
Figure 13 presents the main counterfactual results. There are a few important takeaways. Emissions decreased significantly in British Columbia (between 10 and 35%) and moderately in

[17] Using exact hat algebra comes with one caveat. I only recover plant-level counterfactual differences in log outcomes. While this reflects average plant-level changes, it does not recover aggregate counterfactual outcomes, which would require observing plant-level productivity.

Quebec. However, the results do not indicate a statistically significant impact on emissions leakage to unregulated plants. This result is seemingly at odds with counterfactual changes in output. Although the emissions reduction is twice as large as the output reduction in B.C., suggesting significant oil-to-gas substitution, the tax caused a non-trivial increase in marginal cost and reduction in output.

Nevertheless, this is not associated with any reallocation of output towards unregulated plants. I cannot reject the hypothesis that output varieties are gross complements against the alternative of gross substitutes. Indeed, if output varieties are gross complements, unregulated plants may suffer from the increase in regulated plants' marginal cost. If output varieties are neither gross complements nor gross substitutes, unregulated plants' output doesn't change.

In the next section, I decompose emissions changes in three channels following the decomposition presented in Equation 10 to better understand this lack of carbon leakage. Lastly, the tax did not cause any statistically significant change in profits. Part of the tax was passed through to higher output prices.



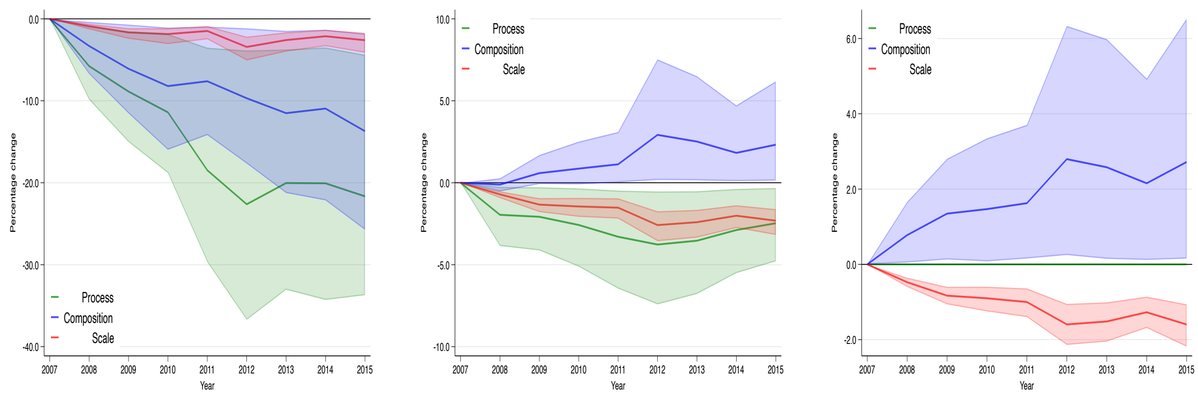
(a) Emissions (b) Output (c) Profits

Figure 6: Impacts of the Carbon Tax by Province

Notes: This figure presents percentage changes in factual relative to counterfactual emissions, output, and profits across regulated and unregulated provinces. Shaded areas represent 95% bootstrap confidence intervals, accounting for two-step estimation noise. In panel 15c, I sometimes get that regulated plants' profits increased. When the bootstrap estimate of ρ is less than one, plants' output varieties become gross complements, and unregulated plants suffer from the increase in regulated plants' marginal cost. If regulated plants have lower baseline input costs (for instance, due to technologies relying more on natural gas than oil), they may even benefit from the policy.

6.1 What Channels are Driving Results? Emissions Decomposition

In Figure 7 and Table 6, I show that the lack of carbon leakage in unregulated provinces can be attributed to a combination of factors. First, the tax caused a composition effect, whereby consumers shifted their expenditures towards products from unregulated plants. However, the aggregate price index across all varieties increased, pushing consumers to purchase less and decreasing aggregate production by 1-2%. Statistically, I do not find that one effect dominates the other, and the net impact on carbon leakage remains insignificant. Second, regulated plants remained relatively competitive. The primary driver behind emissions reductions was the process channel, where plant-level oil-to-gas substitution caused a 14.8% reduction in emissions. Lastly, British Columbia only accounts for 9% of plants. Any policy specific to B.C. must be very large to trigger a significant reallocation of output to other provinces. Thus, the upper bound on emissions leakage remains below 3% in Figure 13.



(a) British Columbia (b) Quebec (c) Unregulated Provinces

Figure 7: Impacts of the Carbon Tax by Province: Emissions Decomposition

Notes: This figure presents percentage changes in factual relative to counterfactual emissions, decomposed into three channels defined in Equation 10. Shaded areas represent 95% bootstrap confidence intervals, accounting for two-step estimation noise. There is no process channel in unregulated provinces because, by construction, relative fuel prices did not change. Results in Quebec are similar to unregulated provinces because the carbon tax was much smaller in Quebec, so it can be considered “unregulated” vis-à-vis British Columbia.

6.2 Robustnes

6.2.1 Unobserved Inputs

One potential criticism of this approach is the assumption that only fuels enter the plant’s production function. In Appendix A.6, I relax this assumption by augmenting the production function to include a composite input that captures all other unobserved inputs (e.g., labor, materials, capital). Under standard assumptions, I show that these unobserved inputs do not affect the counterfactual results. I derive sufficient conditions that justify this abstraction: the production function must be log-separable between the fuel composite and the other composite input (i.e., Cobb-Douglas), and the composite input must be flexibly adjustable at a price that can vary across industries,

		British Columbia	Quebec	Unregulated provinces
GHG	*Total*	-24.26***	-2.84**	0.61
		(5.39)	(1.02)	(0.72)
	Scale	-1.87**	-1.61	-1.01
		(0.68)	(1.69)	(0.91)
	Composition	-8.11	1.35	1.69
		(26.76)	(7.29)	(23.57)
	Process	-14.81***	-2.50**	NA
		(4.40)	(0.93)	
Output		-9.90***	-0.33	0.61
		(2.97)	(0.65)	(0.72)
Profit		-3.23	0.49	0.61
		(3.38)	(0.65)	(0.72)
Observations		547	1,573	4,445

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Average Effect of the Carbon Tax on Outcomes (% Change)

Notes: This table reports the average effect of the carbon tax following the 2008 implementation for selected variables in different provinces. The decomposition of total GHG emissions into the scale, composition and process categories directly comes from Equation 10 and should be interpreted by the following statement: "*On average, plants changed their emissions by x% due to changes in aggregate consumer demand (scale), changes in competitiveness relative to other plants (composition), and changes due fuel substitution (process).*" There is no process effect for unregulated plants because these plants saw no changes in relative fuel prices.

regions, and years.[18] If the price of the composite input varies by province, I must control for it in the demand elasticity regression. I construct an input price index using various data sources from Statistics Canada, as detailed in Appendix A.6.2, and find that controlling for this index leaves counterfactual results virtually unchanged.

6.2.2 Electricity

Another potential criticism of this approach is that I abstract from electricity substitution, which could play a key role in industrial decarbonization. By definition, switching to electricity shifts emissions to power plants, which are not in the NPRI data. To address this, I collected historical electricity consumption by province at the industrial level from the Comprehensive Energy Use Database (CEUD) (Natural Resources Canada, 2023). In Figure 8, I show that the industrial share of electricity use remains relatively stable over time in provinces subject to the carbon tax. This observation suggests limited substitution away from fossil fuels between 2008 and 2015. Most cross-province differences appear permanent: plants in Quebec use significantly more electricity due to the abundance of cheap hydroelectric power. This lack of trend in electrification contrasts with

[18]Results in this paper should thus be interpreted as long-run impacts, where all inputs can adjust freely, rather than short-run scenarios with fixed inputs.

the trend for fossil fuels. After the tax, the share of natural gas increased in both provinces, the share of oil declined in Quebec, and the gap between the share of gas and oil increased in both provinces.

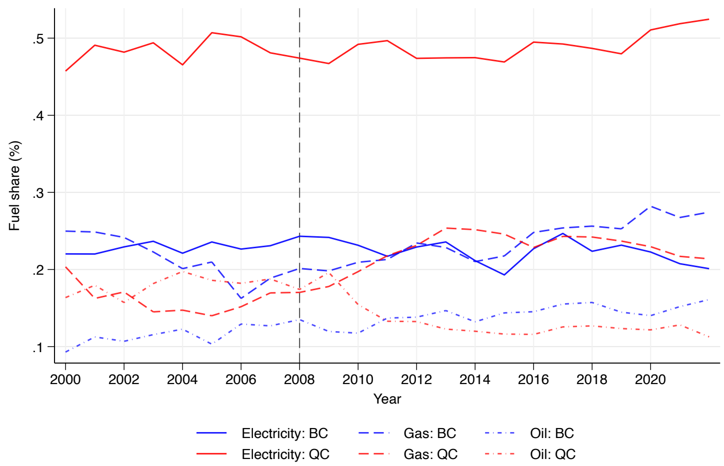


Figure 8: Aggregate Fuel Shares—Regulated Provinces

Notes: This figure plots the aggregate fuel shares in different provinces from the Comprehensive Energy Use Database (CEUD). I only show the fuel shares for the fuels discussed in the paper. I do not show other fuels such as solid fuels (coke, coal, wood), so fuel shares do not necessarily sum up to 1.

Although Figure 8 abstracts from industry and plant-level heterogeneity, the substitution between natural gas and oil, emphasized throughout this paper, remains a relevant margin of adjustment that electrification does not entirely obfuscate. Electrifying heavy manufacturing industries such as steel, aluminum, and cement remains a significant challenge due to the extreme heat required in some production steps, often exceeding 1,500°C (Bataille et al., 2018). Substitution within fossil fuels continues to offer a meaningful channel of adjustment that can complement, rather than be replaced by, electrification efforts.

6.2.3 Other Regulation

As discussed in Section 4.2.2, Alberta introduced a particular carbon pricing mechanism targeting plants emitting more than 100 kiloton of CO_{2e} in 2007 and Quebec introduced its cap-and-trade system targeting plants emitting more than 25 kilotons of CO_{2e} in 2013. In Appendix A.7, I re-estimate everything excluding targeted plants by both policies. Overall, I find remarkably similar results. The interfuel elasticity of substitution is higher, closer to 3 as found by Papageorgiou et al. (2017) and Jo (2024), and the elasticity of demand is slightly lower. However, counterfactual outcomes are almost identical.

6.2.4 Trade Costs

The final potential criticism is that I abstract from interprovincial trade barriers by assuming a single unified market. In this context, the results on carbon leakage represent an upper bound—what we might expect in the absence of trade frictions between provinces. Since I find no evidence of carbon leakage, introducing trade costs will unlikely change the conclusions.

7 Conclusion

In this paper, I build a production model where manufacturing plants can substitute between different fuels and compete across multiple regions. Using a panel of publicly available emissions data from Canadian plants, I can recover counterfactual emissions, output, and profits of regulated and unregulated plants following British and Quebec carbon taxes implemented in 2007 and 2008, respectively.

The primary findings indicate substantial emissions reductions in British Columbia (ranging from 10% to 35%) and moderate reductions in Quebec. Contrary to theoretical predictions of carbon leakage, the analysis reveals no statistically significant shift in production toward unregulated provinces. A detailed decomposition highlights that the absence of leakage is due primarily to aggregate price increases suppressing overall consumer demand and regulated plants' ability to absorb the tax by switching from oil to natural gas. Through the British Columbia and Quebec experiences, the analysis demonstrates that a unilateral carbon tax can effectively reduce emissions without significant negative spillovers to unregulated regions.

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A Appendix

A.1 Preliminary evidence for entry/exit

To investigate entry/exit as a result of the carbon tax, I run a simple difference-in-difference regression with the number of plants as the dependent variable. In both BC and Quebec, the control group comprises plants in all other provinces and the treated period is from 2008 onwards for both provinces. As an asymmetric carbon tax raises the marginal cost of regulated plants relative to the marginal cost of unregulated plants, standard Melitz theory suggests that the minimum productivity required to operate in regulated provinces would increase, decreasing the number of operating plants, and vice versa for unregulated provinces. Hence, the DiD coefficients should be negative. Here, it is positive, which is why I assume that the productivity distribution remains the same after the tax. As discussed in the main text, this result is consistent with multiple findings in the literature.

	(1) British Columbia	(2) Quebec
time	-100.0***	-100.0***
	(2.57)	(2.43)
treated	-97.24***	-21.74***
	(4.19)	(3.38)
DiD	79.40***	71.66***
	(5.55)	(4.47)
constant	242.7***	242.7***
	(1.89)	(1.79)
N	7,888	8,813

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Difference-in-Difference on plant Entry/Exit

A.2 Derivation perceived prices and relative fuel quantities

Starting from the plant's cost minimization problem:

$$\min_{\{q_{fs}\}_{f\in\mathcal{F}}} \left\{ \sum_f p_{fs} q_{fs} \right\} \text{ s.t. } F = \left(\sum_f \lambda_f (q_{fs})^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}$$

$$\mathcal{L} = \sum_f p_{fs} q_{fs} + \mu \left(F - \left(\sum_f \lambda_f (q_{fs})^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)} \right)$$

FOC:

$$p_{fs} = \mu \left(\frac{\lambda_f}{(q_{fs})^{1/\sigma}} \left(\sum_f \lambda_f q_{fs}^{(\sigma-1)/\sigma} \right)^{1/(\sigma-1)} \right) \forall\ f$$

I can divide fuel f's FOC by fuel ℓ's FOC:

$$\frac{p_{fs}}{p_{\ell s}} = \left(\frac{q_{\ell s}}{q_{fs}} \right)^{1/\sigma} \frac{\lambda_f}{\lambda_\ell}$$

Then,

$$q_{fs} = \left(\frac{p_{\ell s}}{p_{fs}} \frac{\lambda_f}{\lambda_\ell} \right)^{\sigma} q_{\ell s}$$

I can plug $q_{\ell s}(q_{fs})$ into the technology:

$$\begin{aligned} F &= \left(\sum_f \left[\left(\frac{p_{fs}}{p_{\ell s}} \frac{\lambda_\ell}{\lambda_f} \right)^{\sigma} q_{fs} \right]^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)} \\ &= q_{fs} \left(\frac{p_{fs}}{\lambda_f} \right)^{\sigma} \left(\sum_f \lambda_f^{\sigma} p_{fs}^{1-\sigma} \right)^{\sigma/(\sigma-1)} \end{aligned}$$

Now I can define perceived prices:

$$\tilde{p}_{fs} = \frac{p_{fs}}{\lambda_f}$$
$$p_s(F) = \left(\sum_f \lambda_f^{\sigma} p_{fs}^{1-\sigma}\right)^{1/(1-\sigma)}$$

Then, I get equation 8 in the paper:

$$F = q_{fs}\left(\frac{\tilde{p}_{fs}}{\tilde{p}_s(F)}\right)^{\sigma}$$
$$q_{fs} = \left(\frac{\tilde{p}_{fs}}{p_s(F)}\right)^{-\sigma} F$$

A.3 Estimation of Fuel Quantities

A.3.1 Estimation of Fuel Quantities — By Industry

Figure 9 is a version of fuel shares comparing my estimates with official statistics by industry. In the paper, I remove the following three industries with limited observations and for which fuel shares are not recovered precisely: wood, fabricated metal, and transportation equipment.

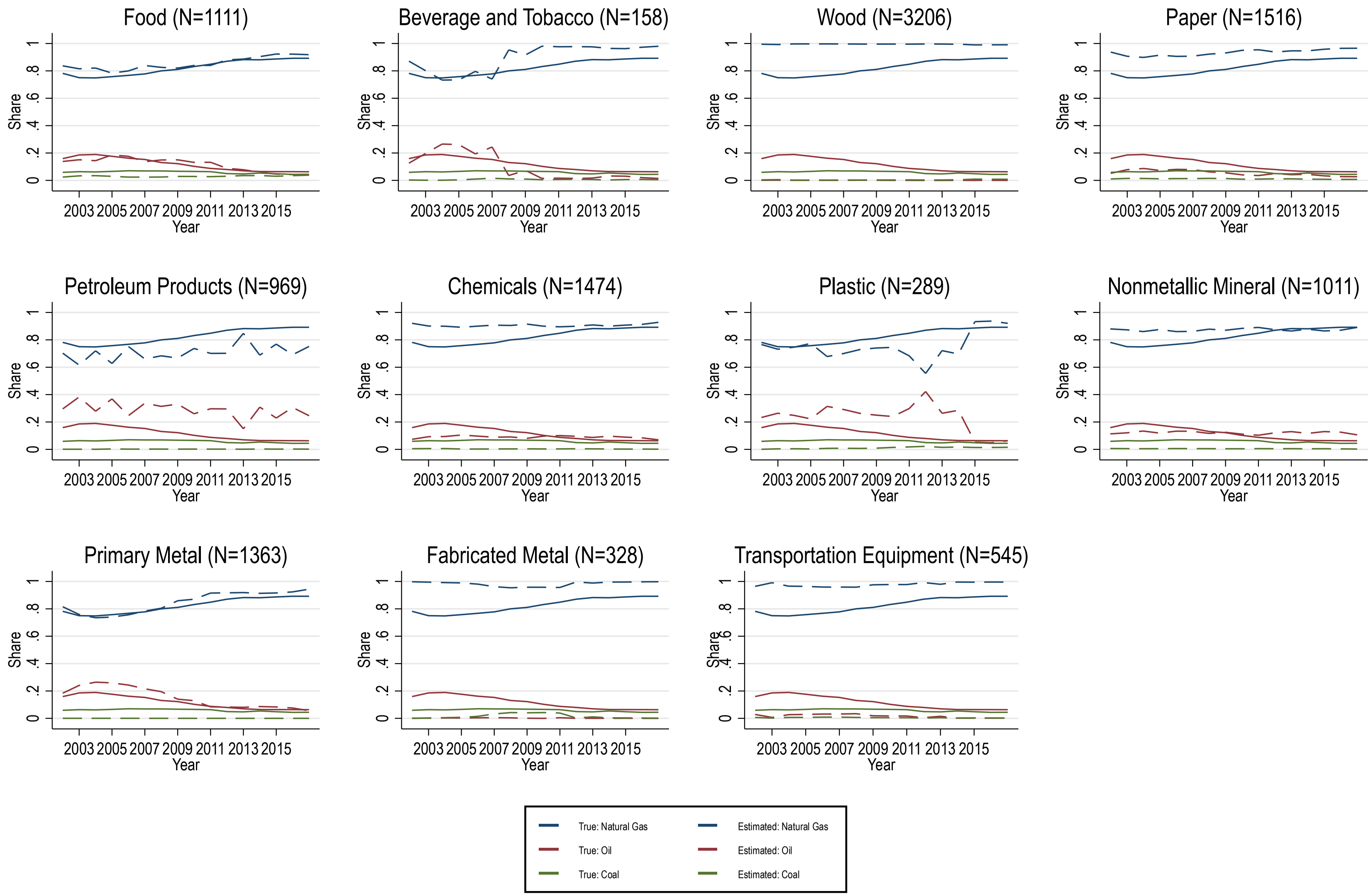


Figure 9: Industrial fuel shares over time — true vs. estimates (main pollutants)

Notes: This figure is constructed by averaging relative fuel shares over time. Dashed lines reflect estimates, whereas solid lines reflect true fuel shares. I construct true fuel shares from Statcan table 25-10-0025-01 (formerly CANSIM 128-0006), which records annual energy consumption by fuel across manufacturing industries from the Annual Industrial Consumption of Energy Survey (ICE). I use linear interpolation for missing values. In the paper, I remove the following three industries with limited observations and for which fuel shares are not recovered precisely: wood, fabricated metal, and transportation equipment.

A.3.2 Estimation of Fuel Quantities Using All Pollutants

In Table 8, Figure 10 and 11, I show a version of fuel estimation that leverages all pollutants released that I observe both in the NPRI and for which the EPA Table AP-42 provides conversion factors. Specifically, it includes all the organic compounds that form total and volatile organic compounds, as well as all speciated metals. The performance of this approach in capturing aggregate and by-industry fuel shares remains virtually identical to the main version.

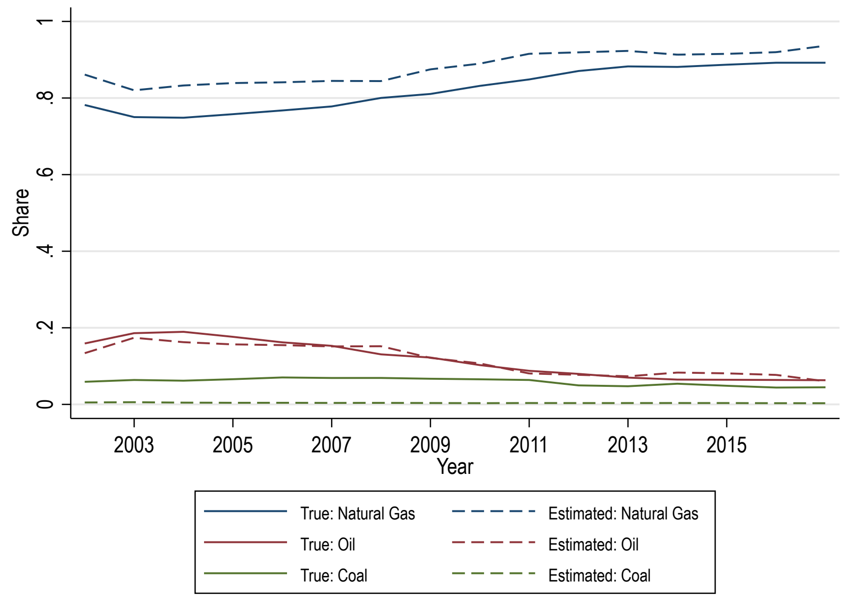


Figure 10: Aggregate fuel shares over time — true vs. estimates (all pollutants)

Notes: This figure is constructed by averaging relative fuel shares over time. Solid lines reflect estimates, whereas blue lines reflect true fuel shares. I constructed true fuel shares from Statcan table 25-10-0025-01 (formerly CANSIM 128-0006), which records annual energy consumption by fuel across manufacturing industries from the Annual Industrial Consumption of Energy Survey (ICE). I use linear interpolation for missing values.

Pollutant	**Element**	**Coal**	**Natural Gas**	**Oil**
Arsenic	As	1.50×10^{-5}	1.95×10^{-7}	9.26×10^{-6}
Naphthalene	C10H8	1.93×10^{-3}	5.95×10^{-7}	7.92×10^{-6}
Acenaphthene	C12H10	2.27×10^{-8}	1.75×10^{-9}	1.48×10^{-7}
Acenaphthylene	C12H8	1.11×10^{-8}	1.75×10^{-9}	1.77×10^{-9}
Fluorene	C13H10	4.05×10^{-8}	2.73×10^{-9}	3.13×10^{-8}
Anthracene	C14H10_1	9.35×10^{-9}	2.34×10^{-9}	8.56×10^{-9}
Phenanthrene	C14H10_2	1.01×10^{-4}	1.66×10^{-8}	7.36×10^{-8}
Fluoranthene	C16H10_1	3.16×10^{-8}	2.92×10^{-9}	3.39×10^{-8}
Pyrene	C16H10_2	1.47×10^{-8}	4.87×10^{-9}	2.98×10^{-8}
Benzo(a)anthracene	C18H12	3.56×10^{-9}	1.75×10^{-9}	2.81×10^{-8}
Benzo(b,j,k) fluoranthene	C20H12	4.90×10^{-9}	0.00×10^{0}	1.04×10^{-8}
Benzo(g,h,i,) perylene	C22H12_1	1.20×10^{-9}	1.17×10^{-9}	1.58×10^{-8}
Indeno(123-cd) perylene	C22H12_2	2.72×10^{-9}	1.75×10^{-9}	1.50×10^{-8}
Toluene	C6H5CH3	1.07×10^{-5}	3.31×10^{-6}	4.35×10^{-5}
Benzene	C6H6	5.79×10^{-5}	2.05×10^{-6}	1.50×10^{-6}
Cadmium	Cd	2.57×10^{-6}	1.07×10^{-6}	2.79×10^{-6}
Formaldehyde	CH2O	1.07×10^{-5}	7.31×10^{-5}	2.31×10^{-4}
Carbon monoxide	CO	2.00×10^{-2}	1.20×10^{-1}	3.51×10^{-2}
Cobalt	Co	4.45×10^{-6}	8.19×10^{-8}	4.22×10^{-5}
Chromium	Cr	4.23×10^{-4}	1.36×10^{-6}	5.93×10^{-6}
Mercury	Me	4.39×10^{-6}	2.53×10^{-7}	7.92×10^{-7}
Manganese	Mn	6.80×10^{-5}	3.70×10^{-7}	2.10×10^{-5}
Nickel	Ni	1.25×10^{-5}	2.05×10^{-6}	5.93×10^{-4}
Nitrogen oxides	NOx	4.63×10^{-1}	7.31×10^{-2}	2.38×10^{-1}
Lead	Pb	2.08×10^{-4}	4.87×10^{-7}	1.06×10^{-5}
PM10	PM10	8.49×10^{-1}	7.41×10^{-3}	4.13×10^{-2}
PM2.5	PM2.5	3.51×10^{-1}	7.41×10^{-3}	2.19×10^{-2}
Selenium	Se	5.79×10^{-5}	2.34×10^{-8}	4.79×10^{-6}
Sulphur dioxides	SO2	1.48×10^{0}	5.85×10^{-4}	1.07×10^{0}
Total Particulate Matter	TPM	1.62×10^{0}	7.41×10^{-3}	5.96×10^{-2}
Volatile organic compounds	VOC	5.94×10^{-3}	5.36×10^{-3}	4.21×10^{-3}

Table 8: Emissions of all pollutants by fuel type (lb/mmbtu)

Notes: This table is constructed by averaging different measures of stationary emissions from the EPA's Compilation of Stationary Emission Factors (AP-42). Natural gas is a more homogeneous fuel than coal and oil. The emissions factors for coal are created by averaging emissions for different coal grades (anthracite, bituminous, subbituminous, and lignite). Similarly, the emissions factors for oil are the average emission factors for different types of fuel oils used in manufacturing, referring to different types of distillate and residual oils.

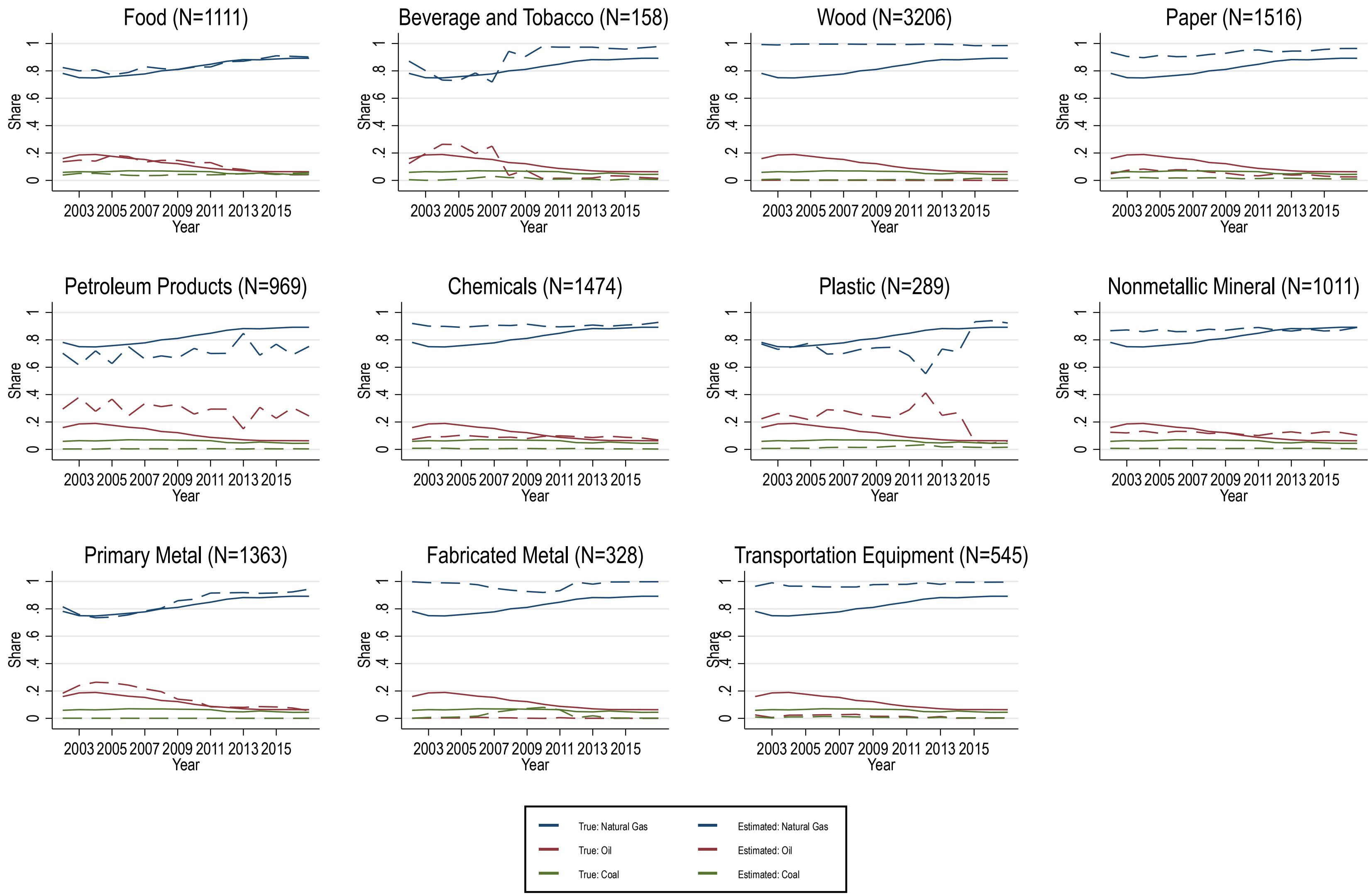
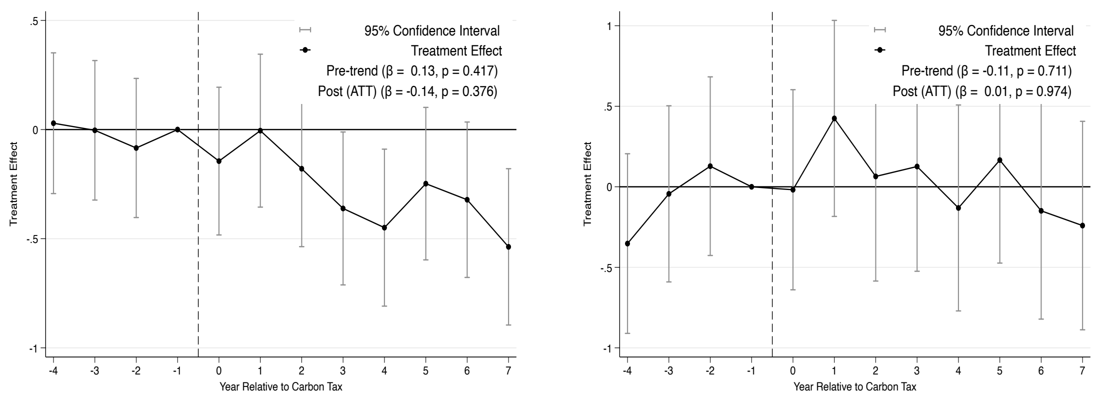


Figure 11: Industrial fuel shares over time — true vs. estimates (all pollutants)

Notes: This figure is constructed by averaging relative fuel shares over time. Dashed lines reflect estimates, whereas solid lines reflect true fuel shares. I constructed true fuel shares from Statcan table 25-10-0025-01 (formerly CANSIM 128-0006), which records annual energy consumption by fuel across manufacturing industries from the Annual Industrial Consumption of Energy Survey (ICE). I use linear interpolation for missing values.

A.4 Event Study Including Coal

In Figure 12, I perform the same event study of relative fuel quantities against the carbon tax as I did with oil relative to natural gas in the main text, but specifically for coal relative to other fuels. Unsurprisingly, I find little evidence that the carbon tax affected relative coal use. I find that the share of coal relative to natural gas decreased in some periods, but the overall effect is insignificant. This result can partly be explained by the fact that coal is rarely used in Canada. Moreover, the carbon tax policy did not specify the tax on coal when looking through official records.



(a) Coal relative to gas

(b) Coal relative to oil

Figure 12: Carbon tax event studies, including coal

A.5 Derivations of Counterfactual Outcomes Using Exact Hat Algebra

Counterfactual changes in log fuel usage are:

$$\ln F'_{it} - \ln F_{it} = -\rho(\ln p'_{it}(\mathcal{F}_{it}) - \ln p_{it}(\mathcal{F}_{it})) + (\rho - 1)(\ln P'_{jt} - \ln P_{jt})$$

The aggregate price index and the log-counterfactual can be defined as:

$$P_{jt} = \frac{\rho}{\rho - 1}\left(\sum_{i \in j}\left(\frac{p_{it}(\mathcal{F}_{it})}{A_{it}}\right)^{1-\rho}\right)^{1/(1-\rho)}$$

$$(\rho-1)\ln(P'_{jt}/P_{jt}) = \ln\left(\frac{\sum_{i\in j}(p_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}{\sum_{i\in j}(p'_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}\right)$$

As one can see, productivity does not disappear. However, observing productivity is not needed. Indeed, notice that each plant's observed relative fuel spending is defined as follows in the model:

$$\theta_{it} \equiv \frac{\sum_{f\in\mathcal{F}_{it}}(p^f_{st}+\tau^f_{st})e^f_{st}}{\sum_{i\in j}\sum_{f\in\mathcal{F}_{it}}(p^f_{st}+\tau^f_{st})e^f_{st}} = \frac{(p_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}{\sum_{i\in j}(p_{it}(\mathcal{F}_{it})/A_{it})^{1-\rho}}$$

Then, counterfactual aggregate prices can be rewritten as a function of observables only:

$$(\rho-1)\ln(P'_{jt}/P_{jt}) = -\ln\left(\sum_{i\in j}\theta_{it}\left(\frac{p'_{it}(\mathcal{F}_{it})}{p_{it}(\mathcal{F}_{it})}\right)^{1-\rho}\right)$$

A.6 Model with Unobserved Inputs

Below, I work out sufficient conditions under which adding a flexible unobserved input does not bias counterfactual estimation. I show that, while including decreasing returns in the fuel composite input does not recover the elasticity of demand ρ separately from returns to scale in the main estimating equation, the net impact on counterfactual outcomes is the same. However, if the price of the unobserved input varies by province, it needs to be included in the main regression.

A.6.1 Derivation of Equivalence Result

I assume a Cobb-Douglas production function between an unobserved composite input X with price p^x_{jst} and fuels F with price $p_{it}(\mathcal{F}_{it})$ as in the paper:

$$Y_{it} = A_{it}F^{\alpha}_{it}X^{1-\alpha}_{it}$$

Given this structure, the profit-maximizing quantity of fuel that a plant demands is:

$$
\begin{aligned}
\ln F_{it} &= \Omega(\alpha,\rho) + \ln(\beta_{jt}C_t) + (\rho-1)\ln P_{jt} + (1-\alpha)(1-\rho)\ln p^x_{jt} - (1+\alpha(\rho-1))\ln p_{it}(\mathcal{F}_{it})) + (\rho-1)\ln A_{it} \\
&= \delta_{jt} + \gamma \ln p^x_{jst} - \beta \ln p_{it}(\mathcal{F}_{it}) + \epsilon_{it}
\end{aligned} \tag{11}
$$

Where $\Omega(\alpha,\rho)$ is some constant. Assuming that the carbon tax did not impact the price of unobserved inputs, counterfactual fuel usage is very similar to before:

$$
\ln F'_{it} - \ln F_{it} = -(1+\alpha(\rho-1))(\ln p'_{it}(\mathcal{F}_{it}) - \ln p_{it}(\mathcal{F}_{it})) + (\rho-1)(\ln P'_{jt} - \ln P_{jt})
$$

The question is whether recovering the reduced form parameter $\beta \equiv (1+\alpha(\rho-1))$ is sufficient to compute counterfactual aggregate price indices. The aggregate price index becomes:

$$
P_{jt} = \frac{\rho}{\rho-1}\Gamma(\alpha)(p^x_{jt})^{1-\alpha}\left(\sum_{i\in j} p_{it}(\mathcal{F}_{it})^{\alpha(1-\rho)} {p^x_{jst}}^{(1-\alpha)(1-\rho)} A_{it}^{\rho-1}\right)^{1/(1-\rho)}
$$

Note that $\alpha(1-\rho) = 1-\beta$. Then, fuel spending shares can similarly be defined as above, and likewise for counterfactual aggregate prices:

$$
\theta_{it} \equiv \frac{\sum_f (p^f_{st} + \tau^f_{st}) e_{fit}}{\sum_{i\in j}\sum_f (p^f_{st} + \tau^f_{st}) e_{fit}} = \frac{p_{it}(\mathcal{F}_{it})^{\alpha(1-\rho)} {p^x_{jst}}^{(1-\alpha)(1-\rho)} A_{it}^{\rho-1}}{\sum_{i\in j} p_{it}(\mathcal{F}_{it})^{\alpha(1-\rho)} {p^x_{jst}}^{(1-\alpha)(1-\rho)} A_{it}^{\rho-1}}
$$

$$
(\rho-1)\ln(P'_{jt}/P_{jt}) = -\ln\left(\sum_{i\in j}\theta_{it}\left(\frac{p'_{it}(\mathcal{F}_{it})}{p_{it}(\mathcal{F}_{it})}\right)^{\alpha(1-\rho)}\right)
$$

It is very easy to show that this will yield the same difference between counterfactual and realized fuel usage as in the baseline that assumes constant returns.

A.6.2 Details of Input Price Construction

To account for robustness to unobserved inputs, I estimate equation 11 using a price index that accounts for labor, capital formation, and non-energy material prices.

For capital, I use the Machinery and Equipment Price Index (MEPI) by Statistics Canada, which varies by industry of purchase, but not by province (Statistics Canada, 2025b). For intermediate materials, I use the Raw Materials Price Index (RMPI) by Statistics Canada, specifically looking at all materials excluding energy (Statistics Canada, 2025d). This price varies by industry but not by province. Lastly, for labor, I collect data on total expenditures and total number of workers in each industry, province, and year from Statistics Canada's Annual Survey of Manufacturing and Logging Industries (ASML) (Statistics Canada, 2025c). I get wages by dividing labor expenditures by the number of workers.

Finally, I construct weights from each price to go into the final input price index using expenditure shares. I collect data on total labor and material expenditures (excluding energy) from the ASML, which varies by industry, province, and year. For capital, I collect capital expenditures by industry, province, and year from Statistics Canada's Annual Capital Expenditures Survey: Actual, Preliminary Estimate and Intentions (CAPEX) (Statistics Canada, 2025e). The final input price index is expressed in 2016 dollars.

A.6.3 Estimation Results

I can only observe this input price index after 2006, so I re-estimate everything using data from 2006 onwards. Results are practically indistinguishable when controlling for this input price index. Removing the first few years of observation slightly lowers the elasticity of substitution and increases the elasticity of demand. Counterfactual changes remain practically indistinguishable.

	(1) Baseline	(2) Baseline + QC control	(3) BM (2015)	(4) BM (2015) + QC control
Elasticity of Substitution: $\hat{\sigma}$	0.906**	1.235**	0.964***	1.236***
	(0.343)	(0.410)	(0.287)	(0.338)
Industry Year FE	Yes	Yes	Yes	Yes
Quebec Financial Crisis Dummies	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Clustered	Clustered
Province FE	Absorbed	Absorbed	Yes	Yes
Observations	2,276	2,276	2,276	2,276

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: IV Estimates of Elasticity of Substitution — Model with Unobserved Inputs

Notes: This table reports estimates of the elasticity of substitution using the carbon tax as an instrument for relative fuel prices. The number of observations represents the number of plants using oil and natural gas in their fuel set. The format is the same as in the main text. Estimation only includes data from 2006 onwards.

	OLS	IV (level) τ_{st}^{co2}	IV (log) $\ln(1+\tau_{st}^{co2})$	IV (IHS) $\text{arcsinh}(\tau_{st}^{co2})$
Elasticity of Demand: $\hat{\rho}$	0.149	1.681	1.660	1.680
	(0.142)	(0.536)**	(0.533)**	(0.536)**
	[0.367]	[0.864]*	[0.856]*	[0.864]*
Industry Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	6,600	6,600	6,600	6,600

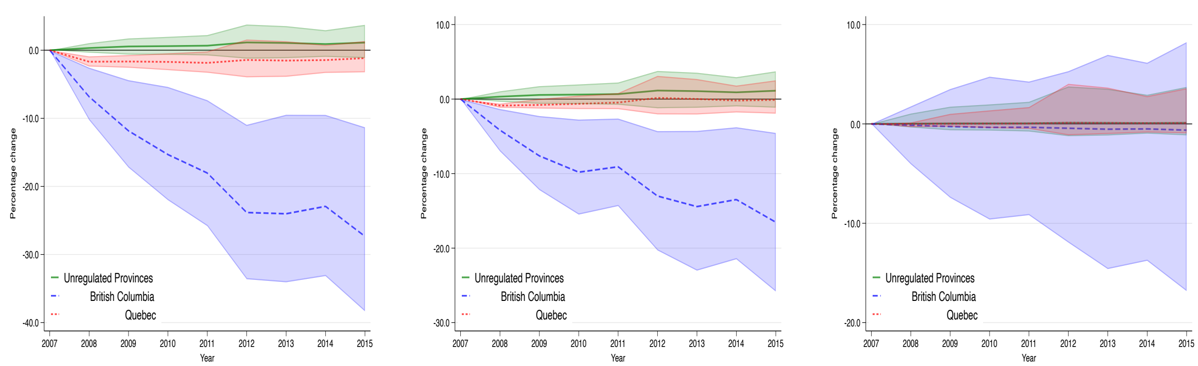
Standard errors in parentheses

Two steps Bootstrap standard errors in brackets

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Elasticity of Demand Estimation — Model with Unobserved Inputs

Notes: The standard errors in brackets account for the estimated variance in the elasticity of substitution. The format is the same as in the main text. Estimation only includes data from 2006 onwards.



(a) Emissions (b) Output (c) Profits

Figure 13: Impacts of the Carbon Tax by Province — Model With Unobserved Inputs

Notes: This figure presents percentage changes in factual relative to counterfactual emissions, output, and profits across regulated and unregulated provinces. Shaded areas represent 95% bootstrap confidence intervals, which account for two-step estimation noise.

A.7 Estimation Results Excluding Plants Targeted by Alberta's Carbon Policy and Quebec's Cap-and-Trade

	(1) Baseline	(2) Baseline + QC control	(3) BM (2015)	(4) BM (2015) + QC control
Elasticity of Substitution: $\hat{\sigma}$	2.385**	3.102**	2.472***	3.036***
	(0.853)	(1.074)	(0.747)	(0.893)
Industry Year FE	Yes	Yes	Yes	Yes
Quebec Financial Crisis Dummies	No	Yes	No	Yes
Province FE	Absorbed	Absorbed	Yes	Yes
Firm FE	YES	YES	Clustered	Clustered
Observations	2,665	2,665	2,665	2,665

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: IV Estimates of Elasticity of Substitution — Excluding Plants Targeted by Other Policies

Notes: This table reports estimates of the elasticity of substitution using the carbon tax as an instrument for relative fuel prices. The number of observations represents the number of plants that are using both oil and natural gas in their fuel set. The format is the same as in the main text.

	OLS	IV (level) τ_{st}^{co2}	IV (log) $\ln(1+\tau_{st}^{co2})$	IV (IHS) $\text{arcsinh}(\tau_{st}^{co2})$
Elasticity of demand: $\hat{\rho}$	0.794	1.202	1.195	1.202
	(0.129)***	(0.422)**	(0.421)**	(0.422)**
	[0.437]*	[0.940]+	[0.934]+	[0.939]+
Industry Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	8,004	8,004	8,004	8,004

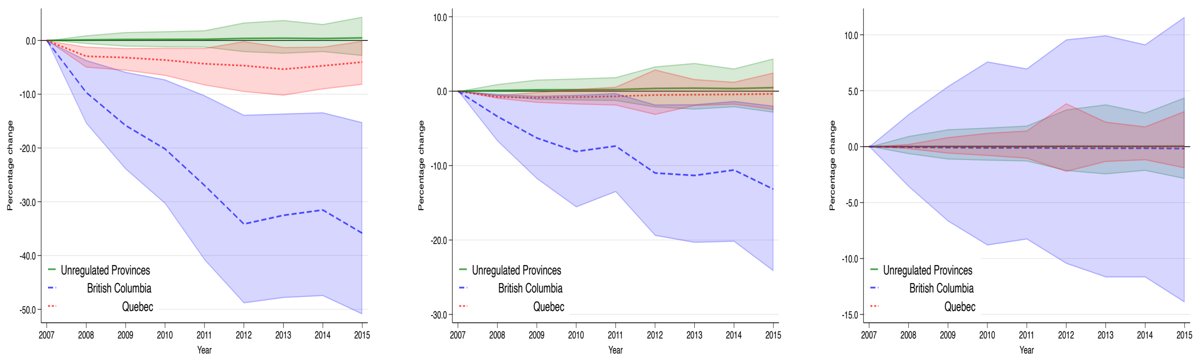
Standard errors in parentheses

Two steps Bootstrap standard errors in brackets

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Elasticity of Demand Estimation — Excluding Plants Targeted by Other Policies

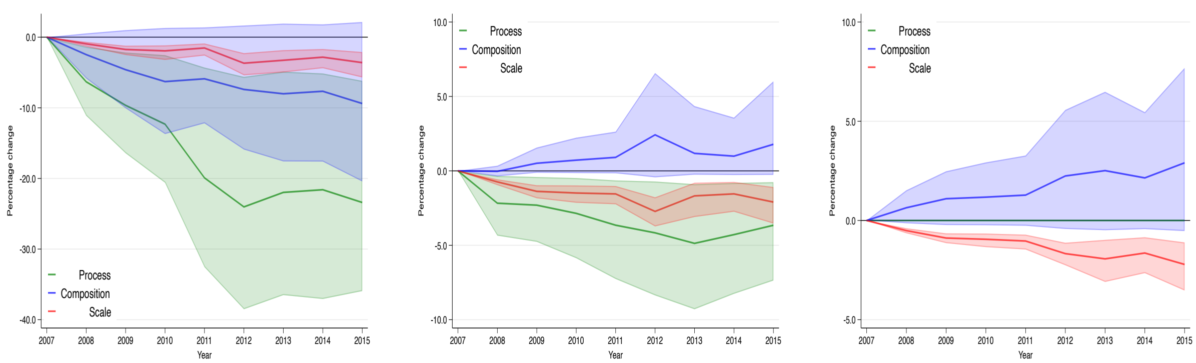
Notes: The standard errors in brackets account for the estimated variance in the elasticity of substitution. The format is the same as in the main text.



(a) Emissions (b) Output (c) Profits

Figure 14: Impacts of the Carbon Tax by Province — Excluding Plants Targeted by Other Policies

Notes: This figure presents percentage changes in factual relative to counterfactual emissions, output, and profits across regulated and unregulated provinces. Shaded areas represent 95% bootstrap confidence intervals, which account for two-step estimation noise.



(a) British Columbia (b) Quebec (c) Unregulated Provinces

Figure 15: Decomposition of Emissions Reduction — Excluding Plants Targeted by Other Policies

Notes: This figure presents percentage changes in factual relative to counterfactual emissions decomposed in three channels. Shaded areas represent 95% bootstrap confidence intervals, which account for two-step estimation noise.