# Do carbon taxes affect economic and environmental efficiency? The case of British Columbia's manufacturing plants

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# Do carbon taxes affect economic and environmental efficiency? The case of British Columbia's manufacturing plants*

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**Abstract:** This paper evaluates the impact of British Columbia's carbon tax on manufacturers' economic and environmental performance in a unified modeling framework that allows for making critical distinctions between efficiency, technical change, and total factor productivity as performance measures. In contrast to most papers that examine environmental policy impacts on either the economy or the environment, our approach combines a by-production model within a stochastic frontier framework to evaluate the tax's impacts on both economic and environmental efficiency. Our findings suggest that a 1.0% increase in the carbon tax improved manufacturers' efficiency in producing desirable output (real sales of manufactured goods) by 0.5%. In addition, the same 1.0% increase in the carbon tax improved manufacturers' environmental efficiency for greenhouse gas (GHGs) and carbon monoxide (CO) emissions by the same amount, 0.2%. However, the carbon tax led to lower environmental efficiency for emissions of nitrogen oxides ($NO_X$), -0.3%. In addition, our use of a rich plant-level dataset reveals considerable heterogeneity in manufacturers' efficiency responses to the tax. Finally, we suggest that lower efficiency levels for undesirable outputs than desirable outputs indicate that the relative cost of adjusting production processes to improve efficiency favors economic efficiency over environmental efficiency.

Keywords: Efficiency; Carbon tax; Stochastic frontier model; By-production model

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## 1. Introduction

A growing body of evidence suggests that environmental policies have had a profound impact on emissions of greenhouse gases (GHGs) and air pollutants, like carbon monoxide (CO) and nitrogen oxides ($NO_X$). In Europe, for example, air pollution from manufacturing fell by between 23%–59% from 1995 to 2008, despite an increase in real shipments of 37% (Brunel (2017)). In the United States, emissions of most air pollutants from manufacturers fell by 52% to 69% from 1990 to 2008, while total real shipments from the sector rose by 35%, primarily due to pollution taxes, according to Levinson (2015). These results were more formally validated by Shapiro and Walker (2018). Moreover, environmental policies have affected the composition of the manufacturing sector (Greenstone (2002)), also contributing to the sector's lower aggregate pollution intensity.

These pollution intensity trends and the extent to which environmental policies impact businesses' performance also appear in the literature for Canada. Gu, Hussain, and Willox (2019) found that total manufacturing emissions of several air pollutants and GHGs in the Canadian manufacturing sector fell substantially between 2004 and 2012. Evidence from Cherniwchan and Najjar (2022) indicates that clean air regulations reduced continuing exporters' export volumes and increased the probability of producers exiting the export market. Najjar and Cherniwchan (2021) show that the decline in pollution intensity from 2000 to 2010 was primarily due to environmental regulation, explaining as much as 61% of the decrease in nitrogen oxides. In addition, they demonstrate that the regulation of some air pollutants significantly influenced patterns of entry and exit among manufacturers.

The carbon tax, implemented by the provincial government of British Columbia (B.C.), has been the focus of several studies that examine various aspects of the tax's environmental or economic impact. Carbone et al. (2020) and Yamazaki (2017), for example, looked at the effect of the tax on employment and found that employment levels fell significantly in the most carbon-intensive sectors but increased in the least carbon-intensive sectors. They estimate that the overall effect of the carbon tax on employment was small.[1]

Using a difference-in-differences approach, Yamazaki (2022) argued that the carbon tax had a

[1] Many other papers consider the impact of B.C.'s carbon tax from the consumer's perspective. See Xiang and Lawley (2019) and Arcila and Baker (2022) for examples.

modestly negative effect on manufacturers in B.C., and found that it generally lowered total factor productivity (TFP) by 1.0% and output by 0.15% annually. However, he also indicated that when the revenues collected from the carbon tax were made revenue neutral by lowering corporate income taxes, TFP increased for the median manufacturing plant by 0.06% due to the positive productivity effect of increased investment in emissions abatement technologies. The period examined, 2004 to 2012, precludes drawing definitive conclusions about the long-run effects of the carbon tax. However, statistically insignificant evidence is presented that the changes in corporate and personal income taxes to make the carbon tax revenue-neutral had a positive impact on TFP one to two years later.

In contrast to these studies, Lutz (2016), who also used a difference-in-differences approach, found that the European Union Emissions Trading System raised productivity in German manufacturing firms. Bernard and Kichian (2021) argue that the revenue-neutral carbon tax had no negative impacts on B.C.'s GDP, while Pretis (2022) finds conflicting results across multiple studies evaluating the effects of B.C.'s carbon tax on employment.

A limitation of many studies is that they examine the effect of environmental policies on economic or environmental performance, but not both.Analysis from [2] Additionally, environmental performance is often defined using a single pollutant or type of pollutant that the environmental policy in question targets, with no consideration given to how the policy may affect emissions of other pollutants. This narrow focus may explain why some studies, including Cifuentes et al. (2001), assume environmental policies uniformly reduce all pollutants. In reality, the adaptations firms make to their production processes in response to environmental policies can positively or negatively impact the generation of other pollutants.

Another limitation in the existing literature appears among studies that examine the impact of carbon taxes or other types of environmental policies on productivity. Their estimation of TFP using standard models makes it impossible to distinguish between the contributions to changes in TFP from technical change and technical inefficiency change. Our findings suggest that manufacturers in British Columbia primarily responded to the carbon tax through efficiency-improving

[2] Najjar and Cherniwchan (2021) is an important exception, examining emissions intensities of four air pollutants and relative changes in manufacturers' output, and entry and exit, but it does not examine impacts on GHG emissions.

adaptations to production rather than through technological change. In addition, we argue that an understanding of the role of efficiency, distinct from technical change, allows for a deeper understanding of the Porter Hypothesis, which we illustrate with a simple example.

Overall, the literature alludes to a broad recognition that environmental policies have important implications for both economic and environmental performance, even if the outcomes are not always clear. Unfortunately, this lack of clarity comes, in part, from the piecemeal analyses employed to evaluate either economic or environmental performance separately, failing to account for the degree to which economic and environmental outcomes are related. In studies focusing on environmental performance, the analysis is often based on emissions of a single pollutant when changes in production processes associated with policy interventions impact emissions of multiple pollutants. We address these shortcomings by using a by-production model in which the production of desirable and undesirable outputs is estimated equation by equation, allowing each output to be represented by its own production technology.

Our by-production model is demanding of the data, requiring that all desirable and undesirable outputs be observed for each plant. Otherwise, including plants with no observations for one or more undesirable outputs would have come at the expense of evaluating the impact of the carbon tax on the joint production of all four outputs at the plant level. Results for net changes in outputs associated with the carbon tax might still have meaning at the industry level. However, the variation of outputs' complementarity or substitutability among plants could not be easily assessed. As a result, we rely on a unique plant-level database that integrates economic and environmental information, where each plant in our sample has observations for all desirable and undesirable outputs.

An appealing aspect of stochastic frontier models is the ease with which researchers can estimate the determinants of changes in inefficiency. This allows us to focus on how the carbon tax affected transient (short-run) economic and environmental inefficiency. However, we also consider how plants' distance from the markets they serve impacted their persistent (long-run) inefficiency.

By employing these methods, we can address our primary question of interest as to whether carbon taxes affect economic and environmental efficiency. We find that B.C.'s carbon tax improved environmental efficiency for emissions of GHGs for manufacturers in the province, consistent with most findings in the literature. Because we use a by-production model to evaluate multiple outputs, our analysis also shows that the carbon tax improved economic efficiency and environmental efficiency for emissions of CO but reduced environmental efficiency for emissions of $NO_X$. This result suggests that reductions in climate change gases can have complex environmental implications. Finally, our stochastic frontier framework allows us to decompose productivity into changes in inefficiency, distinct from changes in technology, and identify the determinants of changes in short-run and long-run inefficiency. Our findings indicate that the carbon tax was, on average, a significant contributor to improving manufacturers' short-run economic efficiency, but with substantial heterogeneity.

The remainder of the paper is organized as follows. Section 2 provides background information about B.C.'s carbon tax. Section 3 discusses the NPRI-ASM database used in the analysis, including a brief description of the determinants of inefficiency. Section 4 describes the theoretical foundations of by-production models and our econometric specification of the stochastic frontier model. Results are presented in Section 5, followed by conclusions in Section 6. Tables of additional results are in Appendix A.

## 2. British Columbia's Carbon Tax

B.C.'s provincial government implemented a carbon tax of C\$10 per tonne of $CO_2$ equivalent GHG emissions on July 1, 2008. After that, it rose by \$5 per tonne every year until it reached \$30 per tonne in 2012. In 2018, the \$5-per-tonne increment resumed each year, except for 2020. The carbon tax reached \$50 per tonne in April 2022 (British Columbia Ministry of Finance (2022)). The carbon tax covers about 77% of all GHG emissions in the province (Ahmadi, Yamazaki, and Kabore (2022) and Harrison (2012)). Exceptions to the carbon tax include fossil fuels for inter–jurisdictional commercial marine and aviation purposes and fuels traveling to or from B.C. for export or commercial marine and aviation purposes. Fuels used in greenhouse operations became exempt starting in 2012, as were fuels used for agriculture in the following year. Biomass fuels and fossil fuels that contribute to fugitive emissions are exempt.

Overall, the introduction of the carbon tax embodies many aspects of an ideal natural experiment, making it exogenous to the internal decisions of manufacturing plants. In particular, the tax was implemented within five months of being announced, limiting polluters' ability to adjust their behavior in anticipation of the change. Moreover, the tax's coverage was comprehensively levied on all sources of carbon emissions from all industries until midway through 2012.

The revenue-neutral aspect of the carbon tax was intended to encourage businesses to substitute away from more carbon-intensive fuels and toward more environmentally friendly energy sources with minimal effect on their income levels due to the tax (Ahmadi, Yamazaki, and Kabore (2022)). Revenues collected from the carbon tax were returned to individuals and businesses through tax reductions or direct transfers. For businesses, the general corporate income tax rate was reduced from 12% to 11% on July 1, 2008. It was further reduced to 10% in 2011. The small business income tax rate was also reduced by one percentage point in 2011 to 3.5% and again in 2012 to 2.5%. In addition, the income threshold between small businesses and general corporations was increased from $400,000 to $500,000.

Because it was applied as a value-added tax on fossil fuels, it is possible to calculate the average effective tax rate for each plant using fuel expenditure data. Since the changes in the carbon tax typically take effect on July 1 each year, the average effective tax was calendarized by taking the average tax of two years to better correspond with the information in the NPRI-ASM dataset.

## 3. Methodology

To analyze the impact of B.C.'s carbon tax implemented on manufacturers' economic and environmental efficiency, we use a by-production model to estimate the joint production of desirable and undesirable outputs, measured as real sales and tonnes of emissions of pollutants, respectively. Incorporating the by-production model into a stochastic frontier framework allows us to jointly estimate economic and environmental efficiency. An additional benefit of this unified model is that it allows us to identify the drivers of transient and persistent efficiency, which are the carbon tax, and manufacturers' distance to markets, respectively. The remainder of this section provides some important concepts of stochastic frontier and by-production models and our motivation to use them in a unified framework in Section 3.1. Section 3.2 presents our econometric approach, which concludes with a discussion about our strategy to manage endogeneity.

### 3.1 A Unified Stochastic Frontier and By-Production Conceptual Model

A strength of stochastic frontier models is that they relax the standard neoclassical assumption that all plants are fully efficient. Common methods used to estimate total factor productivity (TFP), like control function methods in the spirit of Olley and Pakes (1996), equate TFP growth with technological change. Relaxing the full efficiency assumption means that changes in TFP can result from changes in technology (a shift in the production frontier) and changes in efficiency (plants' movement closer to or further from the production frontier, which is not associated with idiosyncratic noise). For example, a decline in inefficiency occurs when a plant increases its desirable output by reducing waste, lowering the misallocation of resources, or both. In contrast, a decline in the inefficiency in producing undesirable output can result from decreased emissions by reducing the misallocation of fossil fuels. In the stochastic frontier framework, inefficiencies associated with desirable and undesirable outputs can be further decomposed into transient (time-varying or short-term) and persistent (time-invariant or long-term) inefficiencies.

Although inefficient use of productive resources may seem to conflict with standard economic assumptions about competitive markets and profit maximization, it only implies that producers' efforts to achieve full efficiency may not be realized and can vary significantly among producers. An extensive overview of the empirical evidence of how common inefficiency is observed as productivity dispersion (Haltiwanger, Foster, and Krizan (2001)); misallocation (Hsieh and Klenow (2009)); zombie firms (Caballero, Hoshi, and Kashyap (2008)); variation in firms' management practices, (Bloom and Van Reenen (2007)); and technology adoption (Griliches (1957) and Bloom et al. (2019)) is presented in Chapter 1 of Grifell-Tatjé, Lovell, and Sickles (2018).

Moreover, acknowledging the role of inefficiency as more than idiosyncratic noise, as stochastic frontier models do, allows for a deeper understanding of the Porter Hypothesis. The relationship between economic inefficiency and the Porter Hypothesis is intuitively illustrated in Brännlund, Lundgren, et al. (2009) and, more recently, in Førsund (2018). A simplified version is presented in Figure 1, where the production of desirable output is measured on the $y$-axis, and undesirable output is on the x-axis. Inefficient production of desirable output, $Y^g$, is represented by point A below the initial production function, $f_0(X)$. In this example, a new environmental policy highlights inefficiencies, inducing producers to reduce undesirable output. In the short run, technology is fixed, but producers can still reach point B if efficiency gains are exhausted. In the long run, investment in new technologies shifts the production function to $f_{CT}(X)$ where fully efficient producers can reach a new point between points C and D (i.e., in the $\overline{CD}$ segment).

Inefficient producers at point A have the strongest incentive to invest in new technologies to survive. Figure 1 illustrates the first-mover advantage, whereby the "leaders" move to the new frontier along the segment $\overline{CD}$. At the same time, the "laggards" remain below point B if they do not acquire new technologies through innovation or adoption. Among plants at point A, those whose inefficiency is predominantly structural and persistent may face the biggest challenges and payoffs from investing in new technologies.

Porter and Van der Linde (1995) present several case studies in which firms' adaptation to environmental regulations led to economic and environmental performance gains that they suggest would not have been achieved otherwise. Recent studies like Bloom et al. (2019) also provide extensive descriptions of the firm characteristics associated with the persistent dispersion of productivity and efficiency measures among plants, which can be substantial even when the plants belong to a larger enterprise. Kube et al. (2019) and Bloom et al. (2010) add that firms with less structured environmental management processes lack the information necessary to identify resource-saving measures.

The point of this simple illustration is to show how the roles of transient and persistent inefficiency are crucial to understanding how gains in economic performance due to an environmental policy are possible. In addition, the illustration indicates that changes in productivity are unlikely to come only from technical change often associated with stronger investments following reductions in income taxes intended to make carbon pricing policies revenue neutral. Therefore, a stochastic frontier model is ideal for distinguishing between changes in efficiency and technical change as sources of TFP growth. However, it is equally important to realize that environmental policies can have unintended negative economic consequences in addition to their environmental implications (Yang, Shao, and Yang (2021)). Therefore, an examination of each plant's multiple economic and environmental outputs is required, for which we employ stochastic frontier and by-production methods as a unified modeling framework.

Our motivation for choosing a by-production model also stems from the need to recognize that environmental policies intended to reduce emissions of one pollutant may lead producers to adapt production processes with positive or negative spillover effects for other pollutants they generate. To illustrate this point, Holland (2011) uses the example of electricity generation from natural gas, which produces emissions of nitrogen oxides ($NO_X$) and GHGs. Electricity producers responded to the implementation of an environmental policy by increasing the combustion temperature to raise the output of electricity generated per unit of natural gas and reduce carbon dioxide ($CO_2$) emissions. However, higher combustion temperatures typically cause $NO_X$ emissions to increase exponentially (Apt and Katzenstein (2011)). In this example, $CO_2$ and $NO_X$ were net substitutes.

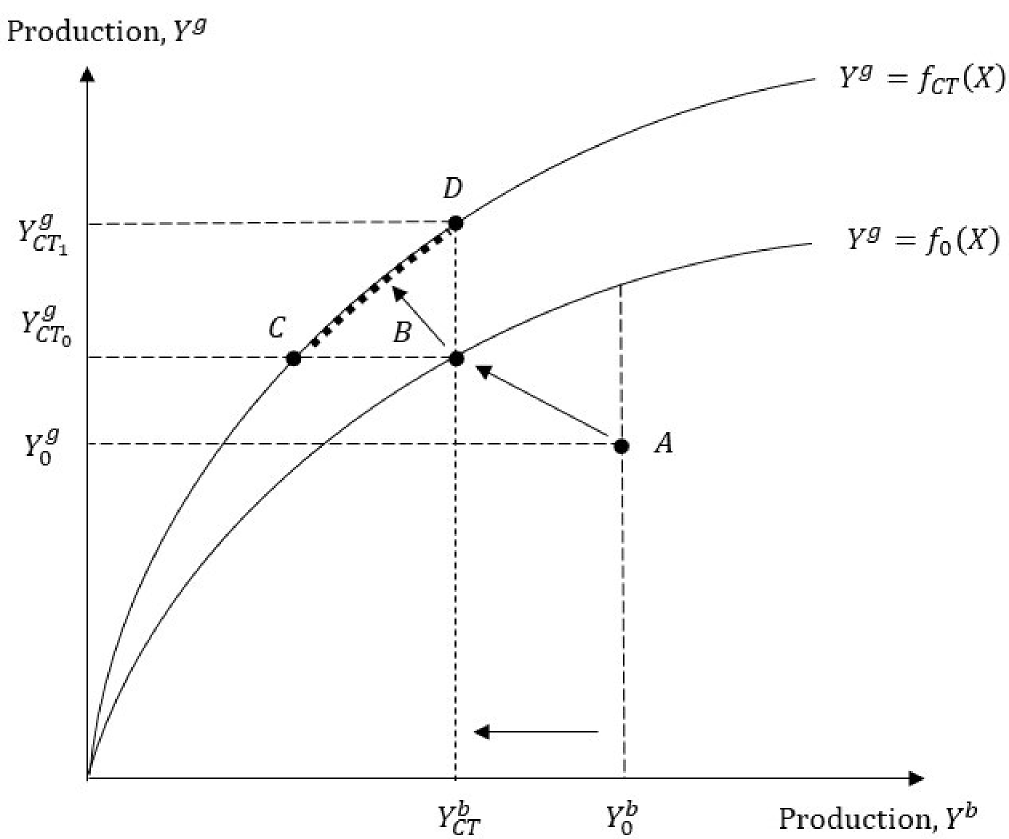


Figure 1: Inefficiency change, technical change, and the Porter hypothesis
Source: Authors' interpretation from (Brännlund, Lundgren, et al. 2009) and (Førsund 2018)

In some cases, the reduction in total fuel consumed may offset the increase in $NO_X$ emissions. Therefore, the overall effect of the environmental policy on $NO_X$ emissions is determined by whether the output effect from reducing fuel consumption is larger than the substitution effect from changes in how the fuel is consumed. Bonilla, Coria, and Sterner (2018) provide a similar example. Environmental policies may also induce fuel switching from gasoline to diesel, for example, which reduces GHG emissions but significantly increases $NO_X$ emissions, according to Stern (2006).

These results suggest that the generation of each undesirable output has a unique relationship with the inputs that produce it. A distinguishing characteristic of by-production models is that they describe the technology used to generate undesirable output as a function of inputs, such as fossil fuels, which are a subset of the inputs used to produce desirable output. Pollution-generating inputs are considered non-rival or joint because their use in producing one output does not prevent the production of the other.

In addition, undesirable outputs have some unique characteristics. These characteristics are

- Production of desired outputs generates undesirable outputs.
- While desirable outputs are freely disposable, undesirable outputs are not.
- Undesirable outputs cannot be substituted for desirable outputs.
- Undesirable outputs can be substituted for some desirable inputs.

In contrast to by-production models, standard models use a single production technology to characterize both desirable and undesirable outputs in a single estimator. To see why this distinction matters, consider the case where good and bad outputs ($Y^g$ and $Y^b$) are produced in isolation. In such a case, economic efficiency in producing good output (output-oriented technical efficiency) is defined as the ratio of actual output $Y^g$ to the maximum possible output $\widehat{Y^g}$. Thus, if $Y^g/\widehat{Y^g} < 1$, there is potential for producing more output without using more inputs. On the other hand, if one uses the cost-minimizing behavior where the objective is to minimize costs without reducing output, the cost efficiency (input-oriented) is defined as the ratio of minimum possible cost to actual cost. In this case, $\widehat{C^g}/C^g < 1$. Thus, if cost efficiency is less than 1, then there is potential for reducing cost without producing less output. Environmental efficiency is defined in the same way, as the ratio of the minimum possible undesirable output $\widehat{Y^b}$ to the actual undesirable output $Y^b$. If $\widehat{Y^b}/Y^b < 1$, there is scope for reducing the production of undesirable output. Note that to distinguish between good and bad outputs, we use the superscripts $b$ and $g$ assuming that these are produced in isolation without any link between the two. The link between $Y^b$ and $Y^g$ is modeled in two ways.

The first approach is to model desirable and undesirable outputs using a single equation production technology in which desirable and undesirable outputs, as well as inputs, enter as arguments. In this case, one cannot separate technical and environmental efficiency. Also, this specification fails to satisfy the axioms of production theory. To understand why, consider how technology is specified by a single equation

$$F(Y^g, X^n, Y^b, t) = A^g, \tag{1}$$

where $F(.)$ is a transformation function, $Y^g$ is a vector $(g \in R^G_+)$ of desirable outputs and $Y^b$ is a vector $(b \in R^B_+)$ of undesirable outputs. $X^n$ is a vector $(n \in R^N_+)$ of factor inputs that generate desirable and undesirable outputs, and $t$ is time, which captures shifts in technology. Finally, $A^g$ includes a constant term as well as the inefficiency and random components of a composite error term. Here we focus on a single desirable output.

The main problems with the single equation model are as follows.

1. Note that monotonicity assumptions on the technology require that $F_{Y^g} \geq 0, F_{X^n} \leq 0$ and $F_{Y^b} \leq 0$, where $F_{Y^g}$, $F_{X^n}$ and $F_{Y^b}$ are partial derivatives of $F(.)$. Since $F_{X^n}$ and $F_{Y^b}$ have the same signs, there is no difference between $Y^b$ and $X^n$ in $F\left(Y^g, X^n, Y^b\right) = A^g$ from a purely mathematical point of view. That is, undesirable outputs can be treated as inputs (Baumol and Oates (1988); Reinhard, Lovell, and Thijssen (1999); Reinhard, Lovell, and Thijssen (2000); and Lee, Park, and Kim (2002)). Since inputs are assumed to be freely disposable, so are undesirable outputs, violating the axioms of production theory.

2. Technical and environmental efficiency are confounded. The technology with input-oriented technical inefficiency is

$$F(Y^g, \theta X^n, Y^b, t) = A^g, \tag{2}$$

where $\theta$ is input-oriented technical inefficiency. Since $X^n$ and $Y^b$ have the same mathematical feature (monotonicity conditions), one cannot determine whether $\theta$ represents the possible reduction in inputs or undesirable outputs.

3. Environmental inefficiency measures the possible reduction in $Y^b$. The model cannot have inefficiency in both $X^n$ and $Y^b$, i.e., one cannot get separate measures of both economic and environmental inefficiency from $\theta$.

The second approach is the recently-developed by-production model proposed by Førsund (2009) and Murty, Robert Russell, and Levkoff (2012), and first applied in Kumbhakar and Tsionas (2016). They discuss theoretical problems of a single equation representation of the technology to model undesirable outputs, and advocate for a by-production technology that separates the production of desirable output from undesirable outputs. Technology for desirable output is specified as $F\left(Y^g, \theta X^n, t\right) = A^g$, which does not include undesirable outputs.[3] By-production technology establishes the link between desirable and undesirable outputs by specifying the technology as $H\left(Y^g, Y^b\lambda, X^r, t\right) = A^b$, where $X^r$ is a subset of $X^n$ that generate $Y^b$ and the inverse of $\lambda$ is environmental inefficiency. Instead of having one technology to produce all the undesirable outputs, we assume that the technology for each undesirable output is separate.

### 3.2 Econometric Modeling

The first equation in our model describes the technology of the production of one desirable output, which is produced using capital, labor, and intermediate inputs. Undesirable outputs do not enter as arguments in this equation. We assume that production technologies for each undesirable output (GHG, $NO_X$, and CO) depend on desirable output and undesirable inputs (fossil fuels).

Technology to produce desirable output (with the plant and time subscripts added) is specified as:

$$Y_{it}^g = f^g(X_{jit}^n, t)\exp(\epsilon_{it}^g) \tag{3}$$

[3] One can use output-oriented inefficiency and write the technology as $F\left(\mu Y^g, X^n, t\right) = A^g$, where $\mu \geq 1$ is output oriented inefficiency.

where $Y^g$ is desirable output, $X^n$ is a vector of $j$ inputs used in the production of $Y^g$, $t$ is time, and $i$ indexes plants. Finally, following Colombi et al. (2014), Tsionas and Kumbhakar (2014), Badunenko and Kumbhakar (2017), we specify $\log A^g_{it} \equiv \epsilon^g_{\text{it}} = v^g_{\text{it}} + v^g_{0i} - u^g_{\text{it}} - u^g_{0i}$ where $\epsilon^g_{\text{it}}$ is a composite error term composed of a random noise term, $v^g_{\text{it}}$, and a firm-specific random effects term, $v^g_{0i}$, which are zero mean random variables. $u^g_{\text{it}}$ is transient (time-varying) inefficiency, and $u^g_{0i}$ is persistent inefficiency, which are both non-negative. Assuming a translog functional form,[4] we can write equation 3 as:

$$\begin{aligned}\log(Y^g_{\text{it}}) =& \beta_0 + \sum_{j=1}^{J} \beta_j \log(X^n_{jit}) \; + \sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jk} \log(X^n_{jit}) \log(X^n_{kit}) + \\ & \sum_{j=1}^{J} \beta_{jt} \log(X^n_{jit}) t + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \beta_{dm} D_m + \beta_{dt} D_t + \epsilon^g_{it} \end{aligned} \tag{4}$$

where $\beta_{\text{jk}} = \beta_{\text{kj}}$ for symmetry restrictions, and $D_m$ and $D_t$ represent indicator variables for manufacturing sub-industries and the period from 2008 to 2012, respectively. Note that the error term $\epsilon^g_{\text{it}}$ in equation 4 is decomposed into four components.

Let the technologies for the undesirable outputs be:

$$Y^b_{it} = f^b(X^r_{jit}, t) exp(\epsilon^b_{it}) \tag{5}$$

where $A^b_{it} \equiv exp(\epsilon^b_{it})$. We assume a translog form again for these technologies and substitute the predicted value of real sales $\widehat{Y^g}$, rather than the actual value $Y^g$, and write equation 5 as:

[4] An alternative to the translog functional form is the Cobb–Douglas. However, it does not satisfy the second order (concavity) condition for profit maximization. Among general flexible functional forms, including the generalized Leontief, the translog has become so ubiquitous and well-understood that it is a commonly accepted standard.

$$
\begin{aligned}
\log(Y^b_{it}) =&\alpha_0 + \alpha_Y \log(\widehat{Y^g_{it}}) + \frac{1}{2}\alpha_{YY}\log(\widehat{Y^g_{it}})^2 + \sum_{j=1}^{R}\alpha_j \log(X^r_{jit}) + \\
&\frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J}\alpha_{jk}\log(X^r_{jit})\log(X^r_{kit}) + \frac{1}{2}\sum_{j=1}^{R}\alpha_{jY}\log(X^r_{jit})\log(\widehat{Y^g_{it}}) + \\
&\sum_{j=1}^{J}\alpha_{jt}\log(X^r_{jit})t + \alpha_t t + \frac{1}{2}\alpha_{tt}t^2 + \alpha_{dm}D_m + \alpha_{dt}D_t + \epsilon^b_{it}
\end{aligned} \tag{6}
$$

where fossil fuels are represented as $X^r$, $\left(X^r \subset X^n \middle| \, r \in R^R_+\right)$. The symmetry restrictions are $\alpha_{jk} = \alpha_{kj}$. The error term $\epsilon^b_{it}$ in equation 6 is decomposed into four components as it was with the production of desirable output in equation 4 $\epsilon^b_{it} = v^b_{it} + v^b_{0i} + u^b_{it} + u^b_{0i}$ where $u^b_{0i} > 0$ and $u^b_{it} > 0$ are persistent and transient environmental inefficiency, respectively. However, an important difference is that the signs in front of the terms $u^b_{it}$ and $u^b_{0i}$ in equation 6 are positive, not negative, to reflect that an increase in environmental inefficiency increases undesirable output. As expressed in equation 4, $v^b_{it}$ and $v^b_{0i}$ are the zero mean random noise and random firm effects terms, respectively.

We estimate the models specified in equation 6 equation by equation to obtain estimates of the technology parameters as well as components of economic and environmental inefficiencies. Distributional assumptions are made on the error components to use the maximum likelihood method (viz., half-normal distribution on the inefficiency components and normal distribution on the noise and firm effects). To explain persistent and transient inefficiency, we allow the variances of the inefficiency components to be functions of some exogenous variables Badunenko and Kumbhakar (2017). We use the following strategy to address the endogeneity of inputs and outputs. Upon consideration of the approaches described in Kumbhakar (2012) to derive an estimating equation in which the regressors are uncorrelated with the error components, we use the predicted value of real sales, $\widehat{Y^g}$, rather than the actual value, $Y^g$, in equation 6.

To estimate the model, we assume that the noise, $v_{\text{it}}$, and the firm-specific random effects, $v_{0i}$, terms are both homoscedastic. This assumption is, however, relaxed for both persistent, $u_{0i}$, and transient, $u_{\text{it}}$, inefficiency components. Persistent and transient inefficiencies for desirable output are expressed, respectively, as:

$$u_{0i} \sim N^{+}\left(0, \sigma_{u0i}^{2}\right) \geq 0 \text{ where } \sigma_{u0i}^{2} = \exp\left(z_{u0i}\gamma_{u0}\right), i = 1, \ldots, N \text{ and} \tag{7}$$

$$u_{\text{it}} \sim N^{+}\left(0, \sigma_{\text{uit}}^{2}\right) \geq 0 \text{ where } \sigma_{\text{uit}}^{2} = \exp\left(z_{\text{uit}}\gamma_{u}\right), i = 1, \ldots, N. \tag{8}$$

Here $z_{u0i}$ denotes the vector of time-invariant variables that determine the variance of the persistent inefficiency (variance of random effects). The term $z_{\text{uit}}$ denotes the vector of variables that determines the variance of the transient inefficiency. Because the efficiency indices are $TE_{u0i} = \exp\left(-u_{0i}\right)$ and $TE_{uit} = \exp\left(-u_{\text{it}}\right)$, their rates of change due to changes in $z_{u0i}$ and $z_{\text{uit}}$ (i.e, $\partial \log TE_{0i}/\partial z_{u0i}$ and $\partial \log TE_{uit}/\partial z_{uit}$) are given by $-\partial u_{0i}/\partial z_{u0i}$ and $-\partial u_{\text{it}}/\partial z_{\text{uit}}$. Marginal effects are approximated at the mean values of $-\partial E(u_{0i})/\partial z_{u0i}$ and $-\partial E\left(u_{\text{it}}\right)/\partial z_{\text{uit}}$, respectively. Since the assumed distributions of inefficiencies are half-normal, the marginal effects can be derived from $-\sqrt{(2/\pi)}\partial\sigma_{u0i}/\partial z_{u0i}$ and $-\sqrt{(2/\pi)}\partial\sigma_{uit}/\partial z_{\text{uit}}$, respectively. Hence, the determinants of the variance of the levels of inefficiency are also the determinants of the levels of efficiency. The determinants of persistent and transient inefficiency are defined similarly to produce undesirable outputs expressed in equations 5 and 6.

A model that comprises technology and determinants of either economic or environmental efficiencies can be estimated in one step using the classical maximum likelihood (ML) approach Colombi et al. (2014) or the maximum simulated likelihood (MSL) method Filippini and Greene (2016). The details of estimation are provided in Colombi et al. (2014) and Filippini and Greene (2016) as well as Badunenko and Kumbhakar (2016). We estimate efficiencies following Badunenko and Kumbhakar (2017), who relate the production frontier technology to the dual cost frontier technologies, using a single-step MSL method that allows heterogeneity in the four random error components. Estimating the four equations as a seemingly unrelated regressions (SUR) system would generate more precise estimates. However, as Lai and Kumbhakar (2018) indicate, calculating the marginal effects of the exogenous determinants as part of a closed-form solution for a system of equations with non-symmetric error components is computationally nearly intractable.

## 4. Data

Data for our empirical analysis come from Statistics Canada's linked NPRI-ASM database. It combines information from the National Pollutant Release Inventory (NPRI) and the Annual Survey of Manufacturing (ASM). The database is one of the most comprehensive sources of information on undesirable outputs and production activity available for Canada's manufacturing sector. Our dataset for manufacturers in B.C. is an unbalanced panel that includes 505 observations for 75 plants from 2004 to 2012. These plants are all large emitters of GHGs, CO, and $NO_X$.

The NPRI-ASM database is distinct from other databases because the ASM includes detailed information on fossil fuels essential for calculating GHG emissions at the plant level, in addition to its extensive financial employment information. Combined with the detailed information on releases of pollutants from the NPRI, we can examine how manufacturers' decisions impact their economic and environmental performance related to climate change from GHG emissions and human health impacts from emissions of multiple air pollutants.

From a modest review of the literature for papers with comparable datasets, we found few that include economic and environmental information. One example is the facility-level criteria air pollution data contained in the Toxic Release Inventory (TRI) maintained by the U.S. Environmental Protection Agency, which can be linked with facility-level economic information from the National Establishment Time Series database (NETS). However, these data contain no information on GHG emissions, limiting environmental analysis to air pollutants, as in Cherniwchan (2017). Others, like Yamazaki (2022) and Ahmadi, Yamazaki, and Kabore (2022), use fuel expenditure data to calculate GHG emissions as we do but do not examine the role of air pollutants. Important contributions have been made using aggregate data that combine emissions of GHGs and air pollutants with economic information (Cole and Elliott (2003)). However, as our results indicate, there is considerable heterogeneity at the plant level that is washed away when the analysis is performed using aggregate data.

The NPRI includes information for over 300 pollutants collected by Environment and Climate Change Canada (ECCC) under the authority of the Canadian Environmental Protection Act, 1999 Environment and Climate Change Canada (1999). All industrial plants, including manufacturers that meet or exceed specified criteria and emission thresholds, must report annually to ECCC on any of the more than 300 pollutants (Environment and Climate Change Canada (2015)). Two of the most common air pollutants reported are CO and $NO_X$, which we include in our model as undesirable outputs.

The NPRI inclusion requirements are based on the amount of a given pollutant emitted and the facility's size (measured by employment). In general, large facilities that emit more than a minimum emission threshold are required to report. The minimum emission threshold varies by pollutant. A minimum concentration threshold may be used for certain substances instead of a minimum emission threshold. Facilities that do not meet the inclusion requirements may still voluntarily report to ECCC. The following are the inclusion criteria used for the NPRI:

- Plants employing more than ten workers (full-time equivalent) must report to the NPRI on each pollutant they emit above the minimum emission threshold (or the minimum concentration threshold).
- Plants that employ fewer than ten workers (full-time equivalent) and operate a device that uses a fossil fuel input (e.g., boiler or generator) must report to the NPRI on each pollutant emitted above the minimum emission threshold.
- Plants that employ fewer than ten workers (full-time equivalent) and do not operate a device that uses a fossil fuel input are not required to report to the NPRI.

Any plant that emits less than the minimum emission threshold or the minimum concentration threshold for a given pollutant is not required to report to the NPRI on that pollutant. These thresholds apply to our sample of manufacturers, implying that our results are specific to large emitters of CO and $NO_X$ in B.C.'s manufacturing sector. Therefore, our results may not be representative of all manufacturers in B.C.

The ASM includes detailed information on Canadian manufacturing plants' production activity, such as shipments, employment, salaries and wages, inventories, and goods purchased for resale and commodity data, including consumption of fossil fuels.

An NPRI facility is potentially a smaller unit of observation than an ASM plant. As a result, some plants in the ASM correspond with multiple facilities in the NPRI. When a plant in the ASM is associated with multiple facilities, the pollutant emissions are aggregated to the plant level. We calculated the emissions of carbon dioxide equivalent GHGs using the plant's expenditures on seven fossil fuels, including gasoline, heavy fuel oil, light fuel oil, propane, natural gas, coal, and diesel. Then, to deflate expenditures, we used prices for B.C. to derive fuel volumes (liters, cubic meters, or tonnes) for each of the seven fuels. Finally, we calculated emissions of GHGs for each plant using $CO_2$ equivalent global warming factors for each of the fuels.

An alternative approach to deriving GHG emissions from fuel expenditure data would be to link the direct estimates of GHG emissions collected by the Greenhouse Gas Reporting Program (GHGRP) at Environment and Climate Change Canada. However, the number of plants linked to the ASM and NPRI databases from 2004 to 2012 was too small to produce consistent estimates. In addition, Ahmadi, Yamazaki, and Kabore (2022), who use the same approach as we do to calculate GHG emissions, note that research by Quick (2014), which shows that calculating GHG emissions is more accurate than measurements taken from emissions monitoring systems.

Plant-level data for prices of gross output, capital, labor, and intermediate inputs would be ideal; however, such detailed price information is rarely available. Instead, we relied on industry-level price data from Statistics Canada's Annual Multifactor Productivity Program from Statistics Canada Table 36-10-0217.

### 4.1 Determinants of Inefficiency

Early approaches to estimating inefficiency sought to address the problem of heteroscedasticity by expressing the variance of inefficiency as a function of exogenous factors that are interpreted as determinants of inefficiency (Wang (2002) and Wang and Schmidt (2002)). However, their models did not distinguish between transient and persistent inefficiency components. Consequently, there were no determinants of persistent inefficiency. It is important to include these two components and their determinants because the policy implications of these inefficiencies are different. Persistent inefficiency is usually caused by structural variables that do not change in the short run, while the factors determining transient inefficiency can be changed in the short run.

Several determinants of transient inefficiency were considered to account for economic or environmental shocks that could potentially influence economic and environmental inefficiency. Aside from the provincial government's carbon tax policy, the most relevant economic and environmental shocks experienced by manufacturers in B.C. between 2004 and 2012 were the 2008–09 recession, the 2010 Winter Olympics held in Vancouver, and the mountain pine beetle infestation. Variables used to account for these shocks included industry employment and unemployment rates; levels, rates, and ratios of job creation and destruction; interest rates; and markups estimated following De Loecker and Warzynski (2012). These variables were included in our estimations in their original and logged values. Several specifications combining quadratic and interaction terms were also tried. Only specifications using the carbon tax produced parameter estimates with consistent signs and magnitudes at standard levels of statistical significance. Parameter estimates for other determinants associated with labor and financial markets or profitability were rarely statistically significant and were frequently difficult to reconcile with economic theory. The irrelevance of these time-varying variables suggests that the time and industry dummies sufficiently capture the influence of economic and environmental shocks other than the carbon tax.

Table 1: Summary Statistics

| | Mean | SD |
|---|---|---|
| Sales (Y) | 168,000,000 | 292,000,000 |
| Capital (K) | 26,000,000 | 52,000,000 |
| Labor (L) | 270 | 220 |
| Intermediate Inputs (M) | 115,000,000 | 248,000,000 |
| Gasoline (G) | 15,000 | 67,000 |
| Heavy Fuel Oil (HFO) | 735,000 | 4,877,000 |
| Light Fuel Oil (LFO) | 40,000 | 384,000 |
| Propane (P) | 60,000 | 218,000 |
| Natural Gas (NG) | 150 | 220 |
| Coal (C) | 3,000 | 15,000 |
| Diesel (D) | 387,000 | 341,000 |
| Distance to Markets (DM) | 710 | 570 |
| Average Effective Carbon Tax Rate (CT) | 7.4 | 12.5 |
| Greenhouse Gases (GHG) | 37,000 | 49,000 |
| Carbon Monoxide (CO) | 2,000 | 6,000 |
| Nitrogen Oxides ($NO_X$) | 260 | 420 |

Note: Sales and capital are measured CDN$ 2012. Labor is the number of employees. Fossil fuels are in liters for gasoline, heavy fuel oil, light fuel oil, propane and diesel; cubic meters for natural gas; and tonnes for coal. Emissions of pollutants are in tonnes.

The carbon tax is defined as the average effective carbon tax rate for each plant. It is calculated by multiplying the volume of fuel purchased by the calendarized per-unit-of-fuel carbon tax. Summing the dollar value of the carbon tax paid on each fuel gives the total annual carbon tax paid for each plant. This is the average effective carbon tax. When we divide this amount by the plant's total fuel expenditure (excluding the average effective carbon tax), we get the average effective carbon tax rate, hereafter referred to as the carbon tax. At the time the carbon tax was introduced, 91% of GHG emissions in the province came from three fossil fuels: natural gas (43%), gasoline (24%), and diesel (24%) (British Columbia Ministry of Finance (2008)). The ASM includes expenditure by fuel type by manufacturing plant for these three fuels as well as for coal, propane, light fuel oil, and heavy fuel oil.

Persistent inefficiency is inherently structural and specific to individual manufacturers. Once production for a manufacturing plant is set, the operation is fixed in the short term. For example, firms cannot relocate production without incurring costly adjustments. Indeed, Ahmadi, Yamazaki, and Kabore (2022) suggest that shifting manufacturing activity to other Canadian provinces to avoid the B.C. carbon tax, referred to as carbon leakage, was inconsequential. As a result, distance to markets was an ideal time-invariant determinant to explain persistent inefficiency. It is defined as the distance from individual plants to shipping destinations reported in the NPRI-ASM data set. Unlike the effect of the carbon tax on transient efficiency from 2008 to 2012, the effect of distance to markets is relevant for the entire nine-year period.

The link between distance to markets and economic performance is well established. For instance, Boulhol, De Serres, and Molnar (2008) cite numerous seminal articles indicating that higher transportation and communication costs associated with distance to markets act as an obstacle to both domestic and foreign trade and foreign direct investment, which reduce knowledge spillovers that negatively impact productivity. More recently, Saha and Mishra (2020) reached similar conclusions after controlling for cultural differences. Similar results are found in numerous papers that use spatial autoregressive stochastic frontier methods found in Glass, Kenjegalieva, and Sickles (2016). Distance to markets is equally relevant for producing undesirable outputs as they relate to fuel costs associated with the transportation of physical goods, according to Harrington and Warf (2002).

One other determinant of persistent inefficiency considered was the first year of operation of the plants, which is a time-invariant indicator of how well the manufacturer is established in the market relative to others. However, like many of the discarded candidates for determinants of transient inefficiency, its parameter estimates were seldom statistically significant.

## 5. Results

Our results are derived by estimating equations 4 and 6 for desirable and undesirable output, respectively. Because the primary objective of our analysis is to evaluate the impact of the carbon tax on economic and environmental inefficiency, we present the estimation results for the determinants of inefficiency in Table 2. Although we have described economic and environmental performance in terms of efficiency to keep our discussion more intuitive, it is important to recall that our estimates represent levels of inefficiency. Therefore, positive coefficients imply that the determinant increases inefficiency (reduces efficiency), while a negative coefficient indicates that it contributes to lower inefficiency (higher efficiency). The results for all estimates, including coefficients and standard errors, for desirable and undesirable outputs, are presented in Tables A.1 and A.2, respectively, in Appendix A. In addition, the marginal effects of determinants of transient and persistent inefficiency for each output are presented in Table A.3, also in Appendix A.

The average effective carbon tax rate (CT), though it was introduced in the middle of the sample period, is statistically significant for all outputs and indicates that the carbon tax lowered transient inefficiency for emissions of GHGs and CO. However, it had the opposite effect on transient inefficiency for emissions of $NO_X$.

Table 2: Determinants of inefficiency

| Variable | Sales | GHGs | CO | $NO_X$ |
|---|---|---|---|---|
| log(DM) | -43.772 *** | 0.220 | 0.315 *** | 2.052 *** |
| $\log(DM)^2$ | 4.316 *** | | | -0.161 *** |
| log(CT) | -2.378 *** | -1.086 ** | -0.733 ** | 1.405 * |

Note: * , ** , and *** indicate significance levels of 5%, 1%, and 0.1%, respectively.

The determinant for persistent inefficiency, distance to markets (DM), and its squared term are statistically significant for desirable output and two out of the three undesirable outputs. The mixed signs and the relative magnitudes of the coefficients for DM and its quadratic term for real sales indicate that for relatively short distances, some distance between manufacturers and the clients to whom they ship their goods has some positive effects on their economic performance. However, as distances to shipping destinations increase, being further removed from their clients is detrimental to economic efficiency, i.e., inefficiency increases. The point at which the effect of a marginal increase in distance to markets on economic efficiency turns from positive to negative is difficult to determine.

To better understand the relative importance of each determinant's effect on inefficiency, Table 3 reports the elasticity of inefficiency with respect to each determinant. For example, the elasticity of inefficiency with respect to the carbon tax for sales is -0.52. This means that a 1.0% increase in the carbon tax from the mean (7.4% in Table 1) would be associated with a decrease in short–term inefficiency of 0.52% on average. This relationship can be expressed equivalently as a 0.52% *increase* in *efficiency*. This efficiency gain would translate directly into an $875,000 increase in real sales for an average manufacturer in our sample.

Table 3: Elasticities of inefficiency with respect to determinants

| Output Type | Output | Determinant | Mean | StDev. | Min. | Max. |
|---|---|---|---|---|---|---|
| Desirable Output | Sales | Distance to Market | 5.103 | 4.192 | -11.734 | 11.675 |
| | | Carbon Tax | -0.521 | 0.517 | -1.170 | 0.000 |
| Undesirable Output | GHGs | Distance to Market | 0.110 | 0.000 | 0.110 | 0.110 |
| | | Carbon Tax | -0.237 | 0.236 | -0.534 | 0.000 |
| | CO | Distance to Market | 0.158 | 0.000 | 0.158 | 0.158 |
| | | Carbon Tax | -0.161 | 0.159 | -0.361 | 0.000 |
| | $NO_X$ | Distance to Market | 0.017 | 0.157 | -0.228 | 0.647 |
| | | Carbon Tax | 0.308 | 0.305 | 0.000 | 0.691 |

Note: The elasticities represent the percent change in inefficiency due to a one percent change in the determinants.

The elasticities of inefficiency with respect to emissions of GHGs and CO are -0.24 and -0.16, respectively. They imply that a 1.0% increase in the carbon tax would reduce environmental inefficiency (increase environmental efficiency) for those pollutants by 0.24% and 0.16%, respectively.

The responsiveness of desirable output (real sales) to changes in the carbon tax is represented by the elasticity of -0.52%, meaning a 1.0% increase in the mean carbon tax would be associated with a decrease in transient inefficiency by roughly 0.52%. That is, real sales would increase by 0.52%. Extrapolating to a more realistic 10% increase in the carbon tax would mean transient inefficiency would be reduced by roughly 5.2% on average. The similar sign and magnitude of these two elasticities imply that GHGs and CO are complements, as described by Holland (2011) and Bonilla, Coria, and Sterner (2018). In this sense, $NO_X$ would be characterized as a substitute given that its elasticity is positive (0.31), meaning that a 1.0% increase in the carbon tax would generate a 0.3% increase in environmental inefficiency. These results provide some insight into the magnitude of the spillover effects of the carbon tax on emissions of pollutants that were not directly targeted by the initial policy.

Table 4 provides estimates of environmental efficiency for desirable and undesirable outputs, where the overall efficiency is calculated by multiplying persistent and transient efficiency. The results indicate that the average overall efficiency for producing desirable output among the sample of 75 manufacturers in B.C. is 90.7% for the sample period from 2004 to 2012. The overall efficiency level for desirable output reflects lower short-term (92.7%) efficiency than long-term (97.9%) efficiency. However, the distributions of short and long-term efficiencies are relatively similar.

Table 4: Economic and environmental efficiency

| Output Type | Output | Efficiency Type | Mean | StDev. | Min. | Max. |
|---|---|---|---|---|---|---|
| Desirable Output | Sales | Persistent | 0.979 | 0.092 | 0.411 | 1.000 |
| | | Transient | 0.927 | 0.077 | 0.334 | 0.999 |
| | | Overall | 0.907 | 0.115 | 0.301 | 0.999 |
| Undesirable Output | GHGs | Persistent | 0.962 | 0.004 | 0.953 | 0.978 |
| | | Transient | 0.882 | 0.086 | 0.403 | 0.981 |
| | | Overall | 0.849 | 0.083 | 0.387 | 0.951 |
| | CO | Persistent | 0.324 | 0.146 | 0.047 | 0.631 |
| | | Transient | 0.591 | 0.167 | 0.033 | 0.873 |
| | | Overall | 0.197 | 0.112 | 0.008 | 0.506 |
| | $NO_X$ | Persistent | 0.384 | 0.164 | 0.039 | 0.760 |
| | | Transient | 0.883 | 0.117 | 0.142 | 0.971 |
| | | Overall | 0.339 | 0.151 | 0.031 | 0.730 |

Note: A value of 1.00 represents full efficeincy. Overall efficiency is the product of transient and persistent effciency.

The interpretation for the three undesirable outputs reflects environmental efficiency, where the producer's objective is to minimize emissions of undesirable output as opposed to maximizing sales or desirable output. The highest overall efficiency level among undesirable outputs was 85% for GHGs, followed by just under 34% for $NO_X$, mostly due to relatively low long-term efficiency. Environmental efficiency in CO was substantially lower at just under 20%, which was again primarily attributable to long-term efficiency.

One reason for the relatively low levels of efficiency for undesirable outputs is that producers tend to be more efficient at maximizing desirable output than minimizing undesirable outputs due to differences in profit incentives. This difference implies that the cost of inefficiently generating sales and potentially going out of business is significantly higher than it is for being environmentally inefficient in terms of reducing emissions, for which fines and taxes tend to be comparatively small. Furthermore, it suggests that the cost of emitting GHGs is relatively higher than it is for emitting $NO_X$ and especially CO. The broader environmental policy implication is that firms are more likely to focus on reducing inefficiency (production and environmental) in proportion to the degree that it reduces their profitability.

The information in Table 4 provides a snapshot of average efficiency over the nine-year period for the four outputs. Figure 2 shows that in 2008 when the carbon tax was introduced, short-term efficiency picked up sharply for sales and emissions of GHGs and CO after exhibiting only modest trends or no trend from 2004 to 2007. The sustained increases in short-term efficiency after 2008 for sales, GHGs and CO sharply contrast with those for short-term efficiency for $NO_X$. The trends in long-term efficiency for all outputs were flat, reflecting that, by definition, they are time-invariant. Some minor changes appear due to some manufacturers entering and exiting the dataset. We evaluated the impact of plant entry and exit on our estimates of inefficiency, following Melitz and Polanec (2015) for each output; however, the effects were negligible. As a result, the patterns of change in overall efficiency closely mirror short-term efficiency.

The improvement in short-term economic efficiency provides some support for the Porter Hypothesis, which suggests that well-designed environmental policies increase productivity and innovation (Porter (1991) and Porter and Van der Linde (1995)). However, the Porter Hypothesis is usually viewed through the lens of standard models that assume businesses are fully efficient and cannot respond to economic or environmental shocks by reducing inefficiency not associated

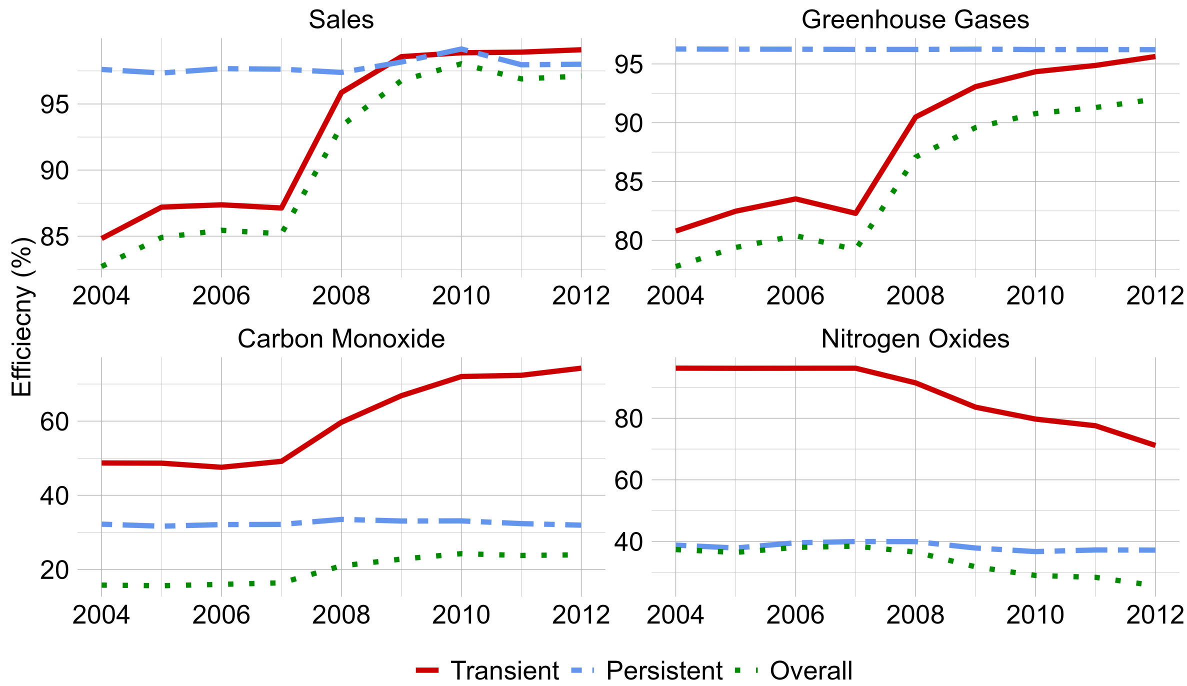


Figure 2: Marginal effects of the carbon tax on output efficiency.
Note: Full efficiency = 100%. Overall efficiency is the product of transient and persistent efficiency. An increase in sales efficiency indicates an increase in sales relative to fixed consumption of inputs without technical change.
Source: Authors' calculations.

with technical change. Therefore, improvements in productivity are assumed to only come from long-term investments in environmentally clean technologies that generate higher productivity and profitability much later.

In response to the carbon tax, improvements in short-term economic efficiency suggest that recognizing inefficiencies and adjusting production processes accordingly involves some cost.[5] Why some plants could improve their efficiency in a relatively short time while others did not may be related to differences in structured environmental management processes that help managers identify resource usage inefficiencies (Bloom et al. (2010)). It is also possible that the cost to adjust production processes to mitigate higher fuel prices was higher than the cost imposed by the carbon tax for some manufacturing plants.

Since the dataset used for this analysis covers a relatively short period after the implementation of the carbon tax, and long-term efficiency is defined as varying only between plants but not over

[5]For an example of how variation in manufacturers' energy efficiency associated with differences in managerial ability helps to explain sub-optimal adoption of energy-efficient technologies known as the "energy paradox" see Boyd and Lee (2019).

time, the results presented here should be regarded as partial support for the Porter Hypothesis. However, improvements in transient (short-term) economic efficiency may lead to longer-term economic efficiency gains from knowledge spillovers between plants within the same enterprise, according to Galloway and Paul Johnson (2016). They found that among electricity generators, the within-firm benefits of such knowledge spillovers of 3%–4% occur at least three years after increased regulatory stringency. Additional spillovers between enterprises may take even longer to affect economic performance.

One of the most important benefits of using plant-level data is that it allows insights into the diversity of outcomes from a single policy. For example, Si et al. (2021) found substantial heterogeneities in output and profits arising from public energy policies across power plants and over time using plant-level data. The importance of heterogeneity in our results is apparent in Figure 3, which shows how responsive individual manufacturers' output efficiencies were to changes in the average effective carbon tax. Each of the four output efficiencies was highly responsive at low levels of taxation for some manufacturers, suggesting that they had relatively little difficulty adapting their consumption of fossil fuels even at low levels of taxation. However, other manufacturers with effective tax rates of nearly 60% showed no response in their output efficiency. For example, the curved red line for GHGs indicates that the marginal effect of the carbon tax (x-axis) on environmental efficiency (y-axis) was positive for all plants and that the size of the effect was relatively large when the effective carbon tax rate was low. The tick marks for the rug plot along the $x$ and y-axes are mostly grouped around the origin. For efficiency, the plot shows that the percentage-point improvement in GHG-related environmental efficiency for many plants was less than one percentage point.

On the other hand, a relatively small number of plants saw their efficiency increase by more than two percentage points, pulling the average level of GHG efficiency up. Along the $x$–axis, the rug plot indicates that there were many plants whose effective carbon tax rates were just above zero and well below the average of 7.4%, indicated by the vertical black line. It also shows that a modest number of plants paid an effective tax rate of over 40%. In this case, the red line representing marginal effects suggests that the adjustment costs of reducing fossil fuel consumption likely exceeded the carbon tax that manufacturers paid.

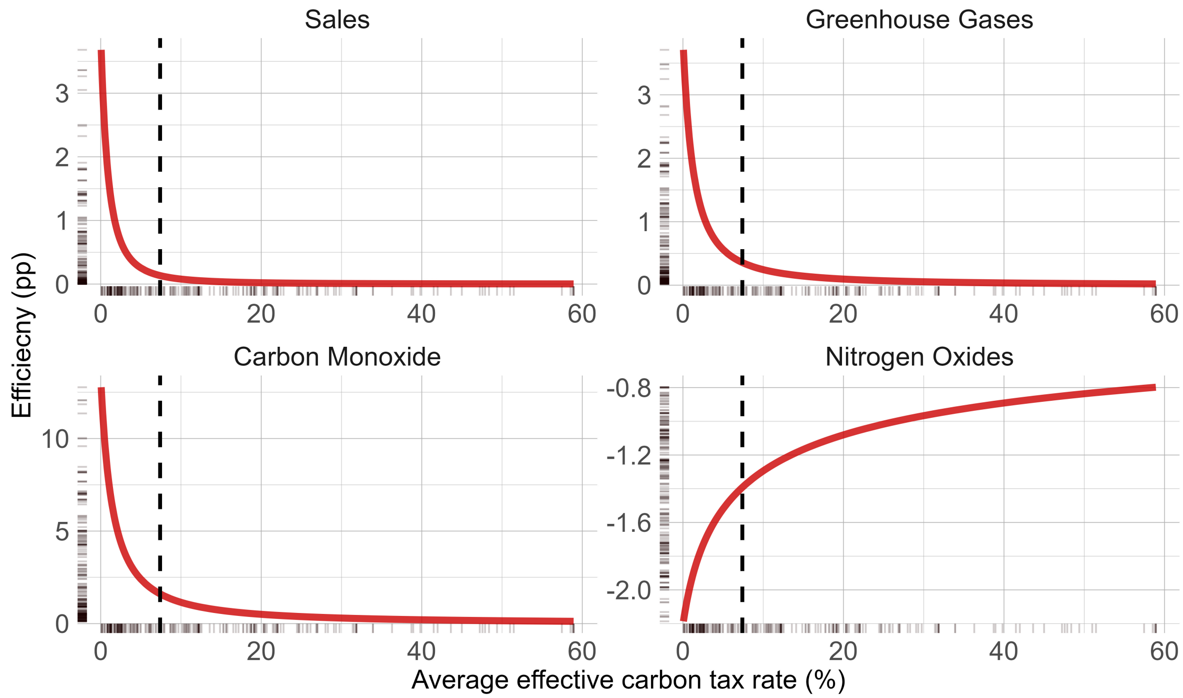


Figure 3: Marginal effects of the carbon tax on economic and environmental efficiency.
Notes: The rug plot on each axis shows a one-dimensional heatmap. The dashed black vertical line is the mean value of the average effective carbon tax.
Source: Authors' calculations.

High average effective carbon tax rates for some plants motivate concerns about the prevalence of carbon leakage. Carbon leakage occurs when stricter environmental standards in one region incentivize businesses to relocate carbon-intensive operations to regions with weaker environmental standards. However, shifting production is generally costly, which may explain why Ahmadi, Yamazaki, and Kabore (2022) found that shifting manufacturing activity to other Canadian provinces to avoid B.C.'s carbon tax was not consequential to their findings.

If the motivation for businesses to improve efficiency is to increase profitability and competitiveness, the levels of efficiency for each output should reflect their relative importance to businesses' bottom lines. Therefore, differences in manufacturers' efficiency responses reflect the cost of paying the tax relative to adjusting production to avoid the tax. Moreover, if efficiency gains for another output, such as desirable output, yield higher returns with a smaller adjustment cost, the incentive to reduce emissions of undesirable outputs becomes even smaller. Consequently, the effectiveness of environmental policies is inextricably linked to both economic and environmental outcomes.

## 6. Conclusion

This paper estimates economic and environmental efficiency using a by-production model in a stochastic frontier framework, markedly improving upon existing models that do not distinguish between the technologies that generate desirable and undesirable outputs. In addition, we demonstrate how exogenous determinants of efficiency can be modeled to explain how environmental policies, like the B.C. carbon tax, can impact economic and environmental performance.

Our key findings are that B.C.'s carbon tax improved environmental efficiency for GHG and CO emissions but reduced environmental efficiency for emissions of $NO_X$ in the province's manufacturing sector. Thus, reductions in climate change gases may come at the expense of lower air quality from higher emissions of smog-producing pollutants such as $NO_X$. Also, the improvement in transient economic efficiency associated with implementing the carbon tax suggests that improving economic and environmental performance are not strictly in opposition to each other.

Another implication from our findings is that the responsiveness of businesses to carbon taxes is not uniform. For example, some manufacturers showed greater capacity to adapt their production processes and technologies while others did not, forcing them to absorb the higher energy costs or find efficiencies unrelated to reducing fuel consumption. This finding implies that efforts to improve environmental outcomes should also consider using plant-level data, when possible, to understand distributional impacts.

Finally, businesses focused on improving the economic and environmental efficiency for desirable and undesirable outputs do so according to how it can improve their profitability and competitiveness. Therefore, the wide disparity of efficiency levels for undesirable outputs relative to those for desirable output indicates that the cost of adjusting production to avoid the carbon tax likely exceeded the cost of paying the carbon tax for many manufacturers.

An area for future research could include econometric methods to estimate by-production models as a system of equations as a seemingly unrelated regressions (SUR) system to generate more precise estimates or as a system approach described by Kumbhakar (2012) to mitigate endogeneity issues further.

## 7. Appendix A

**Table A1: Regression results: Undesirable output**

| | Coef. | p-value |
|---|---|---|
| Intercept | 6.730 | 0.000 |
| log(K) | 0.015 | 0.052 |
| log(L) | 1.428 | 0.000 |
| log(M) | 0.094 | 0.000 |
| t | -0.167 | 0.009 |
| $0.5\log(K)^2$ | 0.005 | 0.000 |
| $0.5\log(L)^2$ | 0.101 | 0.000 |
| $0.5\log(M)^2$ | 0.061 | 0.000 |
| $0.5t^2$ | 0.006 | 0.004 |
| Ind1 | 0.036 | 0.435 |
| Ind2 | 0.100 | 0.024 |
| Ind3 | 0.150 | 0.005 |
| Ind4 | 0.189 | 0.000 |
| Yr08-12 | -0.106 | 0.000 |
| log(K)log(L) | 0.000 | 0.913 |
| log(K)log(M) | 0.000 | 0.213 |
| log(K)t | 0.000 | 0.292 |
| log(L)log(M) | -0.099 | 0.000 |
| log(L)t | -0.002 | 0.618 |
| log(M)t | 0.008 | 0.080 |
| v0: Intercept | -5.603 | 0.000 |
| u0: Intercept | 77.888 | 0.000 |
| u0: log(DM) | -43.772 | 0.000 |
| u0: $\log(DM)^2$ | 4.316 | 0.000 |
| vi: Intercept | -5.078 | 0.000 |
| ui: Intercept | -3.330 | 0.000 |
| ui: log(CT) | -2.378 | 0.000 |

Note: Regression results for the determinants of inefficiency shown here include four intercepts representing the four components of the composite error term. They are the random persistent (v0), persistent inefficiency (u0), random transient (vi) and random inefficiency (ui) terms.

Table A.2: Regression Results: Undesirable Output

| | GHGs | | CO | | $NO_X$ | |
|---|---|---|---|---|---|---|
| | Coef. | p-value | Coef. | p-value | Coef. | p-value |
| Intercept | 12.261 | 0.000 | 77.833 | 0.000 | 4.864 | 0.117 |
| log(Y) | -1.562 | 0.000 | -8.879 | 0.000 | -1.325 | 0.000 |
| log(G) | -0.125 | 0.000 | 1.462 | 0.000 | 0.139 | 0.603 |
| log(P) | 0.171 | 0.000 | 0.963 | 0.000 | -0.310 | 0.041 |
| log(NG) | 4.360 | 0.000 | 3.474 | 0.013 | -1.046 | 0.521 |
| log(C) | 0.209 | 0.000 | 0.683 | 0.336 | 2.416 | 0.000 |
| log(D) | 0.003 | 0.906 | -1.986 | 0.000 | 0.624 | 0.000 |
| log(LFO) | -0.228 | 0.000 | -0.738 | 0.039 | 0.206 | 0.356 |
| log(HFO) | -0.102 | 0.000 | -0.509 | 0.112 | -0.258 | 0.000 |
| t | -0.006 | 0.815 | -1.653 | 0.000 | -0.284 | 0.524 |
| $0.5\log(Y)^2$ | 0.135 | 0.000 | 0.499 | 0.000 | 0.135 | 0.000 |
| $0.5\log(G)^2$ | 0.017 | 0.007 | 0.040 | 0.027 | -0.028 | 0.058 |
| $0.5\log(LFO)^2$ | 0.154 | 0.000 | 0.209 | 0.000 | -0.035 | 0.329 |
| $0.5\log(P)^2$ | 0.017 | 0.000 | 0.029 | 0.060 | 0.029 | 0.004 |
| $0.5\log(NG)^2$ | 0.149 | 0.000 | -0.008 | 0.904 | 0.088 | 0.057 |
| $0.5\log(C)^2$ | 0.037 | 0.000 | -0.008 | 0.663 | 0.039 | 0.000 |
| $0.5\log(D)^2$ | 0.000 | 0.985 | 0.106 | 0.000 | 0.037 | 0.007 |
| $0.5\log(HFO)^2$ | 0.037 | 0.000 | 0.000 | 0.997 | -0.017 | 0.010 |
| Ind1 | -0.005 | 0.257 | 0.011 | 0.492 | -0.022 | 0.021 |
| Ind2 | -0.378 | 0.000 | 2.812 | 0.000 | -0.594 | 0.041 |
| Ind3 | -0.166 | 0.002 | 3.210 | 0.000 | 1.074 | 0.003 |
| Ind4 | -0.811 | 0.000 | -1.412 | 0.001 | -2.771 | 0.000 |
| Yr08-12 | -1.249 | 0.000 | -0.997 | 0.292 | -0.955 | 0.002 |
| $0.5t^2$ | 0.089 | 0.041 | 0.157 | 0.409 | -0.216 | 0.013 |
| log(Y)log(G) | 0.001 | 0.595 | -0.091 | 0.000 | 0.005 | 0.779 |
| log(Y)log(P) | -0.015 | 0.000 | -0.062 | 0.000 | 0.004 | 0.688 |
| log(Y)log(NG) | -0.211 | 0.000 | -0.2 | 0.027 | 0.054 | 0.554 |
| log(Y)log(C) | -0.027 | 0.000 | 0.003 | 0.955 | -0.145 | 0.000 |
| log(Y)log(D) | -0.009 | 0.000 | 0.118 | 0.000 | -0.047 | 0.000 |
| log(Y)log(LFO) | 0.015 | 0.000 | -0.007 | 0.775 | -0.020 | 0.178 |
| log(Y)log(HFO) | -0.001 | 0.551 | 0.028 | 0.215 | 0.024 | 0.000 |
| log(Y)t | 0.006 | 0.037 | 0.082 | 0.000 | 0.019 | 0.442 |

Note: Regression results for the determinants of inefficiency shown here include four intercepts representing the four components of the composite error term. They are the random persistent (v0), persistent inefficiency (u0), random time-varying (vi) and random inefficiency (ui) terms.

Table A.2: Regression results: Undesirable output, continued

| | GHGs | | CO | | $NO_X$ | |
|---|---|---|---|---|---|---|
| | Coef. | p-value | Coef. | p-value | Coef. | p-value |
| log(G)log(P) | -0.001 | 0.393 | 0.004 | 0.153 | 0.000 | 0.916 |
| log(G)log(NG) | 0.003 | 0.200 | 0.016 | 0.198 | -0.004 | 0.519 |
| log(G)log(C) | -0.004 | 0.032 | -0.003 | 0.689 | 0.006 | 0.225 |
| log(G)log(D) | 0.000 | 0.670 | -0.003 | 0.557 | -0.011 | 0.000 |
| log(G)log(LFO) | 0.002 | 0.095 | -0.002 | 0.672 | 0.002 | 0.514 |
| log(G)log(HFO) | 0.001 | 0.543 | 0.008 | 0.063 | 0.001 | 0.623 |
| log(G)t | 0.004 | 0.001 | -0.008 | 0.119 | 0.008 | 0.004 |
| log(P)log(NG) | 0.001 | 0.731 | -0.002 | 0.852 | -0.001 | 0.946 |
| log(P)log(C) | -0.005 | 0.004 | -0.052 | 0.000 | -0.012 | 0.131 |
| log(P)log(D) | 0.002 | 0.111 | 0.007 | 0.236 | 0.008 | 0.045 |
| log(P)log(LFO) | 0.000 | 0.811 | 0.000 | 0.986 | -0.003 | 0.149 |
| log(P)log(HFO) | -0.002 | 0.002 | 0.002 | 0.588 | 0.001 | 0.755 |
| log(P)t | -0.001 | 0.398 | -0.006 | 0.243 | 0.000 | 0.930 |
| log(NG)log(C) | -0.069 | 0.000 | -0.032 | 0.120 | 0.041 | 0.013 |
| log(NG)log(D) | -0.011 | 0.000 | -0.032 | 0.027 | 0.011 | 0.050 |
| log(NG)log(LFO) | 0.000 | 0.998 | 0.022 | 0.161 | 0.005 | 0.487 |
| log(NG)log(HFO) | -0.016 | 0.000 | 0.010 | 0.451 | -0.011 | 0.027 |
| log(NG)t | -0.003 | 0.370 | 0.003 | 0.806 | -0.008 | 0.457 |
| log(C)log(D) | -0.001 | 0.650 | -0.002 | 0.743 | -0.006 | 0.200 |
| log(C)log(LFO) | 0.023 | 0.000 | 0.001 | 0.956 | -0.010 | 0.214 |
| log(C)log(HFO) | -0.003 | 0.041 | -0.003 | 0.648 | 0.004 | 0.463 |
| log(C)t | -0.002 | 0.320 | 0.004 | 0.650 | -0.005 | 0.297 |
| log(D)log(LFO) | -0.006 | 0.000 | 0.012 | 0.014 | -0.001 | 0.803 |
| log(D)log(HFO) | -0.003 | 0.000 | -0.009 | 0.001 | -0.005 | 0.001 |
| log(D)t | -0.004 | 0.001 | -0.002 | 0.717 | 0.003 | 0.179 |
| log(LFO)log(HFO) | -0.001 | 0.502 | 0.006 | 0.125 | 0.005 | 0.015 |
| log(LFO)t | -0.004 | 0.081 | 0.008 | 0.290 | -0.007 | 0.083 |
| log(HFO)t | 0.004 | 0.000 | 0.003 | 0.573 | 0.002 | 0.542 |
| v0: Intercept | -2.550 | 0.000 | 0.668 | 0.000 | -0.613 | 0.000 |
| u0: Intercept | -7.398 | 0.006 | -0.836 | 0.115 | -5.350 | 0.000 |
| u0: log(DM) | 0.220 | 0.616 | 0.315 | 0.000 | 2.052 | 0.000 |
| u0: $\log(DM)^2$ | | | | | -0.161 | 0.000 |
| vi: Intercept | -3.945 | 0.000 | -0.763 | 0.000 | -1.809 | 0.000 |
| ui: Intercept | -2.683 | 0.000 | 0.320 | 0.429 | -6.057 | 0.009 |
| ui: log(CT) | -1.086 | 0.006 | -0.733 | 0.003 | 1.405 | 0.018 |

Note: Regression results for the determinants of inefficiency shown here include four intercepts representing the four components of the composite error term. They are the random persistent (v0), persistent inefficiency (u0), random transient (vi) and random inefficiency (ui) terms.

Table A.3: Marginal effects of the determinants on inefficiency

| Output Type | Output | Determinant | Mean | StDev. | Min. | Max. |
|---|---|---|---|---|---|---|
| Desirable Output | Sales | Distance to Market | -0.006 | 0.056 | -0.491 | 0.002 |
| | | Carbon Tax | -0.090 | 0.087 | -0.180 | 0.000 |
| Undesirable Output | GHGs | Distance to Market | 0.000 | 0.000 | 0.000 | 0.000 |
| | | Carbon Tax | -0.059 | 0.053 | -0.113 | 0.000 |
| | CO | Distance to Market | 0.001 | 0.002 | 0.000 | 0.011 |
| | | Carbon Tax | -0.182 | 0.158 | -0.343 | -0.001 |
| | $NO_X$ | Distance to Market | 0.001 | 0.004 | 0.000 | 0.024 |
| | | Carbon Tax | 0.020 | 0.007 | 0.008 | 0.027 |

Note: The marginal effects show the change in inefficiency due to a one percentage point change in the average effective carbon tax rate or a one kilometer change in distance to markets.

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