Does technological advancement really lead to industrial pollution reductions? A spatial-dynamic analysis of industrial firms in Canada

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Agricultural and Resource Economics

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Abstract

The environmental performance of an economic unit is often conditioned on both time (in terms of its history of pollution) and space (in terms of the performance and capital investments for abatement by its neighbors). However, despite large literatures addressing each of these linkages individually, consideration of dynamic and spatial linkages within a unified empirical framework is rare. This study jointly explores the temporal and spatial linkages that determine tradeoffs and complementarities in environmental performance of industrial firms. Our main objective is to examine the role of research and development (R&D) in reducing pollution. While technological change has been purported as a key driver in policy efforts to achieve a clean energy future, the question of `to what extent does technological change directly reduce GHG-emissions?' has received little attention. This omission is striking given the amount of resources that is channeled into R&D at both the national and regional levels throughout the world. To identify the role of technological change on pollution, we pair a panel dataset on carbon dioxide equivalent emissions from Canadian industrial firms for the period 2004-2016 with provincial R&D expenditures over the same period. We control for key observed determinants of firm activity at the industry-sector and provincial levels based on a thorough review of the theoretical and empirical literature. We control for the remaining unobserved firm-level and time-specific influences using two-way firm and time fixed effects, respectively. We estimate our model using a generalized method of moments Spatial Lag Dynamic Panel Data framework which simultaneously accounts for the dynamic panel data problem and the endogenous spatial lag problem. Our results show that technological change measured through R&D expenditures, significantly reduces industrial firm emissions, yet not at a rate that is not large enough to counteract the boost in emissions associated with increased economic activity during periods of

economic growth. Further, physical-science based R&D is more effective than social-science based R&D in reducing emissions. In addition, our study finds evidence to suggest that both the dynamic and spatial spillovers of pollution effects have a significant, positive effect on firm-level pollution. Thus, much of the empirical literature on this issue, which focuses either on dynamics or on spatial linkages but not both, suffers from a misspecification error.

Preface

This thesis is an original work by Ashley Sarauer. No part of this thesis has been previously published. The empirical model referred to in Chapter 4 was designed by myself, with the assistance of Dr. Sandeep Mohapatra.

Dedication

To my mother

Acknowledgements

I have received an immense amount of support and mentorship from the economists and professors I have worked with at the University of Alberta. I would like to thank my supervisor Sandeep Mohapatra for his patience, guidance and encouragement in all stages of my thesis project. I would also like to thank Vic Adamowicz, my committee member, for his advice and support in the completion of my research project. I am extremely grateful to both of these individuals for the excellent guidance they provided me with in terms of training and advice over the course of my project.

Many thanks also go out to the staff and students I had the pleasure to meet while in the Department of Resource Economics and Environmental Sociology. I am very grateful for the friendships and kind conversations that helped get me through the program. I would also like to thank my mentors- Alicia Entem, Barry Anderson and Yvette Thompson- for the coffee chats and the initial advice that led me to pursue this path to become an environmental economist in the first place. Many thanks to you all.

Finally, I would like to thank my friends- Danielle, Devon and Jenn- and my very supportive family- for your support through the challenges and triumphs involved in seven years of education at the University of Alberta. Thank you to my family for being such an overwhelming wealth of positivity for me. I would not be in this place without your love and support. Thank you finally to my boyfriend, James, and his family- who always believed in me and further encouraged my confidence and resilience. Much love to you all. Thank you for being there for me and believing in me. Words cannot describe how much it means to have you all in my life.

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Chapter 1: Introduction

1.0 Introduction and Objectives

Most scientists agree that a key way to avoid the costs of climate change, air pollution and other key indicators of environmental degradation is to reduce our reliance on fossil fuels as an energy source. However, many national and global institutions have been slow to respond with meaningful environmental policy actions because of the likelihood of negative impacts on economic growth. The lack of political will to respond to this issue is evident through the failure of international agreements to reduce greenhouse gas (GHG) emissions, such as the Kyoto Protocol (National Post, 2011).

In Canada, a key national policy approach, taken in lieu of a dramatic restructuring of the energy system, is an emphasis on investment in research and development (R&D) (Popp, 2016). Further, clean technology is increasingly purported as a leading instrument to combat climate change (Government of Canada, 2019a). The success of this approach relies on the assumption that technological advancements reduce emissions and are economically feasible. However, regulators are often unsure of how much technological improvement is ultimately achievable (Freeman and Haveman, 1972). In fact, the actual proportion of R&D spending to gross domestic product (GDP, chained dollars) has increased only marginally from 2004 (1.68% of GDP) to 2016 (1.76% of GDP) within Canada (Author's computation; Stats Canada, 2019).

Surprisingly, there is very little direct empirical evidence on the effect of R&D on pollution, and the linkage of R&D efforts to pollution remains unclear in many empirical contexts (Jaffe et al., 2003). While R&D policies are justified by themselves to contribute to secure technological potential and economic growth (Trajtenberg, 1990; Lichtenberg, 1992), an even stronger justification for investment in R&D can be built if these expenditures can be shown to causally reduce GHG-emissions. Scholars argue that the relationship between technological change and pollution requires more unpacking, and that there is an urgent need for research exploring the specific channels through which technological change is linked to environmental quality outcomes (Arimura et al., 2007; Jaffe et al., 2003).

Understanding the impact of policies that encourage technological change on the environment requires a deeper understanding of both the economic factors that drive 'environmentally-friendly technology' adoption, as well as the complex interplay of technology adoption, pollution abatement and economic growth. For instance, some scholars argue that the linkages between economic growth and the environment can only be assessed by careful consideration of dynamics (Mohapatra et al., 2016). Kolstad and Krautkraemer (1993) show that pollution, the negative externality associated with increased economic activity during a period of economic growth, is likely to accumulate and become more evident in the long run. It is also possible that, due to changes in environmental policy though time, there would be endogenous policy responses that reduce pollution over time. This in turn would impact the net effect of economic growth on the environment. Furthermore, significant evidence from the technological-change literature suggests that facilities can get locked-in to a particular technological regime or become path dependent, as the costs of employing more efficient technology are often high (Goodstein, 1995).

Meanwhile, other scholars argue that linkages between economic growth and the environment can be assessed by careful consideration of spatial spillovers (Cole et al., 2013; Huang, 2018). There is longstanding evidence that spatial effects can contradict or invalidate the results of time series models (Rey and Montouri, 1999). Pollution levels of firms can be spatially correlated for a number of reasons. For instance, 'best practices' in pollution control and technology adoption may be passed between firms via ‘demonstration’ effects (Cole et al., 2013). Through this mechanism, a facility may adjust their own environmental performance in response to neighboring facilities’ environmental performance (Zheng et al., 2014; Zhao et al., 2015; Li et al., 2017; Huang et al., 2017; Cheng, 2016). LeSage and Pace (2009) warn that ignoring spatial correlation of pollution may lead to biased estimations.

Some quantitative studies are beginning to account for the dynamic considerations of pollution outlined in the pollution path persistence literature (Jaffe et al., 2003). However, most fail to account for spatial spillovers of pollution. Even fewer studies in the technological change-environment literature account for spatial spillovers of pollution or integrate both approaches (e.g. Huang, 2018; Zheng et al., 2014).

The first objective of this study is to econometrically estimate the impact of technological change, measured through provincial R&D expenditures in Canada, on pollution by Canadian firms. Secondly, our study aims to provide insight into the mechanism through which technological change influences industrial pollution outcomes by analyzing how different types of R&D expenditures (e.g., physical and social sciences) may have heterogeneous impacts on pollution.

Our approach for modeling pollution is consistent with the economic growth–environment literature, led by Copeland and Taylor (2004) and Antweiler et al. (2001). This literature develops a theoretical model of pollution demand and supply to derive the response of pollution to economic determinants. This recent literature provides a more nuanced interpretation of the economic causal effects of pollution, compared to its previous counterpart, the environmental Kuznets curve (EKC) literature (Grossman and Krueger, 1995). Our introduction of R&D expenditures into this framework draws on the literature on endogenous technological change and sustainable growth. Scholars in this field extend the Schumpeterian growth theory, where R&D efforts lead to an improvement of total factor productivity, thereby lowering the emissions-intensity of production (Hart, 2004; Zhang et al., 2017). This approach is similar to studies such as Cole et al.'s (2005) study that uses a region's technological absorptive capability, proxied through foreign direct investment, as a measure of progress towards lower emission-intensive processes and techniques of production. Since R&D has both public and private qualities, in the absence of firm-level data on 'invention, innovation and diffusion' R&D offers a credible measure of technological improvement (Jaffe et al., 2003).

To examine heterogeneity in pollution impacts across different types of R&D expenditures, we separate out R&D into two variables that explain the 'science types' of the R&D: 'social sciences, humanities and the arts' and 'natural sciences and engineering' R&D expenditures. The two decomposed variables provide more information for assessing the potential technological change channels, and subsequently, the policies that would have the most significant impact on emissions reductions at the level of the firm. For instance, 'natural sciences and engineering' R&D may significantly reduce firm-level emissions through directly reducing the cost of improved capital and machinery, but 'social sciences, humanities and the arts' R&D may achieve the same result through institutional design, as well as through awareness and education programs (Diamond, 1996). Thus, a technological change policy can become more effective at leveraging a pollution reduction outcome (e.g. reducing facility emissions) if the specific factors that influence that outcome (e.g. increasing access to engineered carbon capture and storage technologies; or better education and awareness of the benefits of a technology) are thoughtfully invested in and allocated.

We use a novel spatial-temporal econometric model to estimate the dynamic and spatial spillover effects of pollution and provide insight into how dynamic and spatial linkages influence a firm's pollution decisions. Ours is the first study to consider the impact of R&D expenditures on the environment by simultaneously accounting for spatial and dynamic considerations. We utilize a facility-level panel dataset of carbon dioxide equivalent (CO_2eq.) emissions, which includes observations on 225 Canadian facilities for the period of 2004-2016. The pollution dataset collected annually by Environment and Climate Change Canada includes all Canadian facilities that pollute more than 50 kilotonnes (kt) of CO_2eq. emissions per year. The dataset includes both NAICS sector information and spatial coordinates for the facilities, which allows us to incorporate both industry and geographical spillover considerations into our analysis. We proxy investment in technological change through total expenditures on R&D at the provincial level.

Our study makes three novel contributions. First, we contribute to the recent empirical economic growth-environment literature on the casual effect of technological change on pollution. Ours is the only study that estimates the casual emissions effect of R&D expenditures using a spatial-dynamic approach, which decomposes R&D into heterogeneous subcomponents. Second, by decomposing R&D into science types, our study provides insight into the mechanism through which R&D influences industrial emissions. Lastly, by implementing a generalized method of moments (GMM) spatial lag dynamic panel data model, our study contributes to the empirical literature on spatial spillovers of pollution, which is critical for understanding the role of 'demonstration effects' between large emitters. More specifically, our study provides an estimate of spatial spillovers of pollution or 'emissions-mimicking' behavior that the spatial spillovers literature suggests can exist between neighboring firms (Cheng, 2016).

Our study is a timely analysis for Canada, the ninth largest emitting country in the world (Government of Canada, 2018). In recent years, there has been a growing concern to reduce emissions, with a particular focus on reducing industrial (heavy industry, oil and gas, and electricity sector) emissions, which accounted for approximately 38% of total CO_2eq. emissions in 2016 (Environment and Climate Change Canada, 2018). Between 2007 and 2018, 85% of provinces implemented a carbon pricing regime for large emitters, with the first 'large industrial emitters carbon pricing' regime coming into place in 2007 for Alberta (Read, 2014). Furthermore, the remaining 15% of Canadian provinces have been subject to anticipatory conversations of industrial carbon pricing, as Canadian national climate change priorities were outlined in the *Pan-Canadian Framework on Clean Growth and Climate Change* and formally announced by the Government of Canada in December, 2016. The framework outlined a federal carbon pricing schedule for large industrial emitters that would apply to all provinces effective January, 2019. These national frameworks and agendas to mitigate climate change, only further exemplify how crucial understanding the casual effect of R&D expenditures on emissions reduction outcomes is on the design of climate change policy in Canada.

The rest of the paper is organized as follows. Section 2 presents a review of the economic growth-environment; technological change-environment; and spatial spillovers of pollution literatures and outlines a simple conceptual model for pollution supply and demand. Section 3 describes the data. Sections 4 and 5 present our econometric approach and results, respectively. The final section concludes.

Chapter 2: Literature Review

Our study is related to three interlinking literatures that explain how economic factors influence pollution response. First, the economic growth-environment literature led by Copeland and Taylor (2004) and Antweiler et al. (2001), decomposes the dynamic determinants of pollution response into three distinct categories. This literature suggests that incorporating dynamic determinants of pollution is important, as failing to control for unobserved time effects in pollution response can bias coefficient estimates. Second, the spatial spillovers of pollution literature posits that firm emissions are spatially correlated for a number of reasons and failing to account for spatial effects can invalidate the results of dynamic models. Finally, these two bodies of literature are complimented by studies that look at the economic determinants of pollution, more generally. This final subset of literature is important to consider as omitted variable bias could additionally bias coefficient estimates in our model.

2.0 Dynamics of Pollution Response

Assessing the impact of economic growth on the environment firstly involves careful consideration of dynamics (Mohapatra et al., 2016). The most prevalent literature that explores the dynamic, causal relationship between economic growth and the environment is a literature led by Copeland and Taylor (2004) and Antweiler et al. (2001). This literature develops a theoretical model of pollution demand and supply to derive the response of pollution to economic determinants. In particular, Copeland and Taylor's (2004) study treats pollution as a factor in the production of a dirty good in a small open economy. The demand for pollution depends on the share of dirty goods in total production, and the scale of production in the economy. The supply of pollution depends on regional environmental policies and the technological advances that make the production of a dirty good less pollution intensive. In addition, regional governments can use policy instruments to regulate emissions, as well as incentivize technological advances in the economy (Jaffe et al., 2003). Following a similar theoretical framework, pollution in facility i at time t can be written as:

$$z_{it} = s_{it} e_{it} \phi_{it} \qquad \text{(Eq. 1)}$$

where s_{it} is the scale of production, e_{it} is the emissions intensity of production which depends on the facility's technological emissions reduction capacity (i.e. efficiency of production), and ϕ_{it} is the capital-intensity of production, expressed in relation to labour intensity. Differentiating this expression yields a reduced form that decomposes the total growth effect on pollution into three components:

$$\frac{dz_{it}}{z_{it}} = \frac{ds_{it}}{s_{it}} + \frac{de_{it}}{e_{it}} + \frac{d\phi_{it}}{\phi_{it}} \qquad \text{(Eq. 2)}$$

This equation suggests that the total magnitude of change in pollution is due to changes in these three terms which jointly determine the impact on the environment.

First, the scale effect, $\frac{ds_{it}}{s_{it}}$, captures the increase in pollution as a result of an expansion of economic activity in a region, ceteris paribus. Many studies have found the relationship between GDP per capita and pollution to be significant (Cole and Elliott, 2003; Shafik, 1994; Selden and Song, 1994; Mohapatra et al., 2016; Grossman and Krueger, 1995). The scale effect is assumed to have an unambiguously positive effect on pollution.

Second, the composition effect, $\frac{d\phi_{it}}{\phi_{it}}$, reflects the ratio of dirty goods to clean goods in total production. This effect is motivated by the premise that capital-intensive industries are more pollution-intensive, in general, as they consume more natural resources, such as metal and diesel fuel. In contrast, labour-intensive industries tend to be more environmentally friendly, with cleaner inputs and production procedures (Cole and Elliott, 2005). Thus, the ratio of capital-to-labour is often used to proxy the composition of dirty to clean industries in the economy. Studies suggest the composition effect, measured through the capital-labour ratio, has a positive effect on pollution, although this is not universally resolved in the literature (Mohapatra et al., 2016). The majority of studies suggest the composition effect has a positive effect on pollution.

The final component included in this literature is the technique effect, $\frac{de_{it}}{e_{it}}$, which posits a reduction in the emissions-intensity of production, often due to a substitution of dirty and inefficient technology by more sophisticated and cleaner methods (Grossman and Krueger, 1995). Studies, such as the one by Antle and Heidebrink (1995), propose that we observe the technique effect because the income elasticity of environmental demand is changing through time. Assuming environmental quality is a normal good, this theory suggests that higher incomes are correlated with higher living standards and also a higher preference for environment quality. Thus, the literature suggests this effect is theoretically motivated by rising incomes, or any additional factors, that lead to higher preferences for environmental quality. In theory, these preferences induce higher environmental regulations and more stringent policy that incentivizes pollution abatement methods and improvements in technology that increase the efficiency of production inputs and by-products, thus lowering the emissions intensity of production. The technique effect is assumed to have an unambiguously negative effect on pollution (Antweiler et al., 2001).

While the scale effect and composition effect are expected to increase pollution response, the technique effect is an impactful pollution determinant to study from an emissions-reduction policy perspective, as it acts as the lever that lowers emissions intensity of production through time. For example, a study by Mohapatra et al. (2016) using panel data on GHG emissions in Canada, found that the technique effect, defined as income induced policy response, significantly reduces pollution during periods of growth. The study concludes that the inclusion of the technique effect is important in its own right, as it is ‘one of the few forces that can decouple the inextricable link between economic growth and environmental quality’. In summary, the technique effect captures all incentives (e.g. environmental regulation) for firms to lower the emissions intensity of production through time.

There are three interlinking components that are required to explain how the technique effect lowers emissions intensity at a level of a firm. First, rising incomes may be correlated with a higher preference for environmental quality. Second, the higher preference for environmental quality induces more stringent environmental regulation through time. Finally, more stringent environmental regulation imposes a cost on polluting, which in turn incentivizes firms to either reduce their emissions intensity of production or face the compliance costs associated with the respective policy instrument outlined by their jurisdiction or province (Calel and Dechezleprêtre, 2016; Hicks, 1932; Grossman and Krueger, 1995; Jaffe and Palmer, 1997; Downing and White, 1986).

It should be noted that neither rising incomes, nor the creation of environmental regulation, *directly* reduces the emissions intensity of production with respect to a firm. Instead, the interconnection of higher environmental preferences and more stringent environmental regulation, impose a price signal for facilities to implement more efficient emissions technology, which otherwise would not occur in the absence of these drivers. These incentives are predicted by the induced innovation hypothesis, which suggests that firms, as profit-maximizers, respond to the price incentives associated with increased environmental regulatory costs and are thus, incentivized to implement more efficient technologies through time (Jaffe et al., 2003). Thus, observing the technique effect largely relies on the effective implementation of emissions technology and pollution abatement methods at the level of the firm.

The process of environmental regulation triggering low-emissions technologies in order to offset environmental compliance costs, is additionally described by the ‘Porter hypothesis’ (Porter, 1991). This hypothesis suggests that firms respond to environmental regulation by implementing cost-cutting efficiency improvements and investing in product and/or process innovation that increases total factor productivity and offsets regulatory costs. This hypothesis contrasts with the ‘pollution haven hypothesis’ (McGuire, 1982) which argues that high regulatory costs crowd out productive investment in innovation or efficiency improvements, and eventually results in firm-relocation to jurisdictions with less stringent environmental policies. Several studies provide evidence supporting the Porter hypothesis and the theory that environmental regulation can induce firm-level investment in clean technologies in the long run (Dechezleprêtre & Sato, 2017).

A key challenge in this literature is empirically testing the Porter hypothesis due to difficulty of measuring the extent to which firms face regulatory costs, and subsequently proceed with low-emissions technological changes (Jaffe et al., 1995). Several studies suggest that R&D expenditures is a good proxy for environmental regulation induced technological change, as there is a significant, positive correlation between environmental regulation stringency and the level of R&D spending within industries over time (Calel and Dechezleprêtre, 2016; Jaffe and Palmer, 1997). This observation, in turn, has led to an expansion of studies that explore how environmental regulation can induce investment in R&D and low-emissions technology.

Although many studies have found low-emissions technologies adoption rates are increasing through time (Li and Just, 2018; IRENA, 2018), few studies attempt to quantitatively estimate the casual effect of technological change on emissions at the level of a firm.

The study that comes closest to this objective is Zhang et al. (2017), who use aggregate data on 30 Chinese provinces to estimate the effect of technological progress on carbon emissions. Their study finds that technological progress, measured through total factor productivity growth, significantly reduces provincial carbon emissions. The study, while using a system GMM approach to address endogeneity using lags of the independent variables as instruments, fails to account for the economic determinants of pollution outlined in the recent economic growth-environment literature (e.g. scale, composition, and technique effects). Furthermore, a study by Lee and Min (2015) examined the effects of firm-level 'environmentally-friendly' technological change on carbon emissions of Japanese manufacturing firms' using annual data between 2001 and 2010. Their study defines 'environmentally-friendly' technological change as a firm's expenditures on R&D particularly aimed at environmental purposes. Using an OLS regression model, their study finds that this type of R&D, has a significant, negative effect on firm-level carbon emissions. However, the inclusion of firm-level R&D directly in the facility emissions equation raises concerns about endogeneity.

Our study differs from both of these studies as ours is the first study to consider the impact of R&D expenditures on the environment while simultaneously accounting for spatial and dynamic considerations. Further, we are the first to econometrically estimate the impact of technological change, measured through provincial R&D expenditures in Canada, on pollution by Canadian firms.

2.1 Spatial Spillovers of Pollution

In addition to considering the dynamic impacts of pollution, many scholars argue that assessing the causal impact of economic growth on the environment must involve careful consideration of spatial spillovers (Cole et al., 2013; Huang, 2018). According to this literature, pollution levels of firms can be spatially correlated for a number of reasons. Cole et al. (2013) suggest there are four main reasons why pollution response can be spatially correlated between geographically-proximate facilities. First, location-specific provincial and/or federal environmental regulation can cause firms to have similar pollution intensities. Second, the industry agglomeration literature suggests that comparable pollution intensities tend to concentrate in specific areas due to land-use zoning and other land-use regulation. Third, the 'best practices' theory suggests the most efficient pollution control and technology adoption methods may be passed between firms via 'demonstration' or 'imitation' effects, in order to avoid compliance costs. Finally, the 'yardstick competition' theory suggests firms implement energy efficiency technologies in order to appear 'more progressive' than neighboring facilities and gain social license from consumers.

Through these mechanisms, a facility may adjust their own environmental performance in response to neighboring facilities' environmental performance (Zheng et al., 2014; Zhao et al., 2015; Li et al., 2017; Huang et al., 2017; Cheng, 2016). LeSage and Pace (2009) warn that ignoring spatial correlation of pollution may lead to biased coefficient estimates. While some quantitative studies are beginning to account for the dynamic considerations of pollution outlined in the pollution path persistence literature (Jaffe et al., 2003), most studies fail to account for spatial spillovers of pollution.

The study that comes the closest to exploring the impact of technological progress on the environment, while simultaneously accounting for spatial and dynamic considerations, is a study by Huang (2018). They utilize a dynamic spatial model to analyze the driving forces of China's provincial carbon intensity over the period 2000–2014. They find that technological progress is an important determinant of regional pollution response. However, their measure of technological progress, measured through the ratio of gross domestic product to capital-labour ratio, is likely to be correlated with their scale effect measure (ratio of gross domestic product) and composition effect measure (capital-labour ratio). This correlation may mask the true technological change effect on pollution.

Our study uses a similar spatial lag dynamic panel data model approach as Huang's (2018) study, however we rely on the theory of the technological change-environment literature to motivate R&D expenditures as an empirically-supported measure of technological progress and diffusion, both provincially and through time. Further, our analysis is novel in that it decomposes R&D expenditures into different types of R&D (e.g., physical and social sciences) to test the underlying mechanisms through which technological change impacts firm-level pollution response.

2.2 Additional Determinants of Pollution

In additional to the three key economic levers (scale, composition and technique effects) identified by the economic-growth environment literature, many studies have identified a number of additional economic variables that have a significant effect on pollution response (e.g. Gassebner et al., 2010; Copeland and Taylor, 2004; Lamla, 2009). Our goal in this section is to summarize empirically-supported, additional determinants of pollution that are deemed important to control for, in order to avoid omitted variable bias. Further, including the empirically-supported variables outlined below allows us to test the sensitivity of the casual effect of R&D expenditures on firm-level pollution response.

International Trade

International trade intensity is frequently linked to pollution in the economic growth-environment literature. Similar to economic growth, the trade effect can be disaggregated into three components: a scale effect, a technique effect, and a composition effect. Cole and Elliott (2003) explain that through the scale effect, an increase in trade intensity can result in an increase in the size of an economy, which can occur as a result of liberalization-induced increases in market access. Hence, trade could increase environmental degradation. The opposing view presented by Cole (2004) suggests that an increase in trade could result in greater competitive pressure or greater access to 'greener' production technologies and could thus result in emissions reductions. This body of literature concludes that international trade intensity is a significant determinant of pollution response and may have a positive or negative effect on emissions. We include international trade intensity in our analysis as a control variable.

Foreign Direct Investment

Studies suggest the foreign direct investment (FDI) is also linked to pollution. For example, Antweiler et al. (2001) suggest that international capital transactions may influence pollution. Furthermore, a study by Cole and Elliott (2005) include FDI in their analysis of pollution intensities from US industries. They motivate FDI in their analysis following the work of Van den Bulcke and Zhang (1998), who suggested FDI can result in increased financial resources, new technology, and a skill-upgraded work force for the country on the receiving side of the investment. The results of Cole and Elliott's (2002) dynamic estimation additionally suggest FDI is a significant determinant of pollution. Foreign direct investment is included as a relevant determinant of pollution in our analysis.

Population Density

According to the literature, population density is also a significant determinant of pollution. This is because population density can proxy informal regulatory pressure, as greater lobbying pressure is often correlated with a larger number of people in a particular area (Cole et al., 2013). Further, a study by Stern (2005) argues that a higher population would mean more people are affected by pollution and thus, the benefit of abatement increases. However, additional studies suggest the expected sign of population density is priori ambiguous. For example a study by Klick (2002), using population density as a determinant of pollution, explains that the effect of individual pollution may aggravate when more people concentrate in one area, thus higher population densities leads to increased aggregate pollution. Population density is included in our analysis as a control variable.

Pollution Abatement Expenditures

The economics-environment literature suggests that pollution abatement and R&D are intrinsically linked together (Tsur and Zemel, 2005; Kollenbach, 2015). Studies also suggest that pollution abatement is relatively costly, yet investments in R&D often place downwards pressure on price (Kollenbach, 2015). Jaffe et al. (2005) explains how a policy aimed at reducing pollution has two effects: 1) the present effect of pollution reduction efforts today (pollution abatement expenditures); and 2) the future incentives and investment decisions firms face with regard to technological developments to reduce pollution, often with the goal of achieving them at a lower cost (innovation). Other studies also argue that pollution abatement expenditures may proxy environmental regulation stringency (Levinson and Taylor, 2008). Overall, many scholars argue pollution abatement expenditures are an important determinant of pollution, although it is not unanimous that this proxy captures the full effect of emissions reduction at the level of a firm (Antweiler et al., 2001; Gray and Shadbegian, 2004). For this reason, provincial pollution abatement expenditures is included in our analysis as a control variable.

Education

In the technological change literature, R&D is often cited as a form of ‘knowledge accumulation’ in which facilities learn-by-doing and through time, and implement the most effective technologies to reduce costs (Goulder and Mathai, 2000). However, analogous studies that explore the relationship between economic growth and the environment often capture ‘knowledge accumulation’ through a direct measure of education levels in a region. For example, both Torras and Boyce (1998) and Klick (2002) include measures of education as control variables in their analysis of economic growth and pollution intensity. Both measures of education and technological change are suggested to capture knowledge or technological spillovers. Overall, many scholars deem investments in education an important determinant of pollution (Nieto and Quevedo, 2005; Gertler and Wolfe, 2006). A measure of education is included in our analysis for this reason.

Chapter 3: Data

3.0 Data Source Description

In order to address our objective, this study utilizes facility-level panel data on carbon dioxide equivalent (CO_2eq.) emissions. Our main variable of interest is the level of CO_2eq. emissions from large emitters in Canada for the years of 2004-2016. Despite this data being calculated from input and output uses at the facility and not measured directly, this measure is generally accepted in the literature as a sufficiently precise proxy of air pollution (Lamla, 2009).

The CO_2eq. emissions data is collected from Environment and Climate Change Canada's (ECCC) Greenhouse Gas Reporting Program and accessed through the Open Data Portal. This dataset exists because of the regulatory requirement under Section 46 of the *Canadian Environmental Protection Act* to report GHG emissions as a commercial entity that produces more than 50 kilotonnes of CO_2eq. emissions per year. A complete set of emissions data (in tonnes of CO_2eq.) by facility is available from 2004-2016 from this source. The GHGs comprising the CO_2eq. measure includes: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6). Starting in 2004, facilities that emit the equivalent of 50 kilotonnes (kt) or more of CO_2eq. emissions per year are required to submit a greenhouse gas emissions report to ECCC. Facilities with emissions below 50 kt can voluntarily report their GHG emissions. In 2016, 596 facilities reported their GHG emissions to Environment and Climate Change Canada for 2016, totaling 263 megatonnes (Mt) CO_2eq. An increasing number of firms report each year as a lower reporting threshold was implemented through time. By 2017, the reporting threshold requires any facility emitting 10 kt or more CO_2eq. emissions per year to report to the ECCC.

In our analysis, we analyze the 225 Canadian facilities that report annually for the entire time period of 2004-2016. We confirm that these firms are the same through time by using their unique facility identifier. This means that our emissions panel dataset is balanced. Although balancing the dataset reduces the representativeness of the sample, we acknowledge that this step was completed in order to avoid the introduction of bias associated with ECCC lowering the mandated emissions reporting threshold through time. The ECCC claims that "since 2005, total emissions from all reporting facilities have decreased overall by 5%" (or approximately 15Mt) (Environment and Climate Change Canada, 2017, p.1). However, ECCC does not seem to factor in the consideration that lowering the reporting threshold and calculating the average emissions value with more low-emissions facilities in the pool, would unambiguously result in a lower emissions average. For this reason, we only analyze the 225 firms that have complete $\mathrm{CO_2 eq.}$ emissions observations throughout the 13-year panel.

The $\mathrm{CO_2 eq.}$ emissions dataset also provides spatial information (latitude/longitude coordinates) of the facilities located across Canada and the NAICS industry code for the facility. This allows us to complete a spatial analysis by facility and link economic datasets at both the provincial and sectoral level. More specifically, this information allows us to include a spatial lag of the dependent variable ($\mathrm{CO_2 eq.}$ emissions) in our dynamic panel data regression in order to capture spatial spillovers of facility $\mathrm{CO_2 eq.}$ emissions. The spatially lagged emissions variable is implemented by creating a geographically weighted matrix (weighted based on inverse geographical proximity in kilometres and created using the 'spwmatrix' command in STATA) and using matrix multiplication to create a spatially weighted emissions variable.

Our main variable of interest, technological change, is proxied through gross provincial expenditures on R&D (constant 2007 prices; $ x 1,000,000; total expenditures; all sectors; by science type; by province). This variable was collected from Statistics Canada. All measurements of R&D expenditures include all private and public funders and all performers of the R&D activity for the province. This choice was made due to many scholars suggesting that R&D has both public and private good characteristics (Jaffe et al., 2003). Therefore, the assumption that private and public sectors of the economy can have heterogeneous impacts in terms of technological spillovers is not pursued in this thesis. This data is collected for the years of 2003-2015 (one-year lag of panel). We followed this approach as the empirical literature suggests there can be a lag for the effects of technological change to be realized (Jaffe et al., 2003).

Statistics Canada provides more detailed information on the intended use of R&D expenditures by science type. Thus, we include two variables to capture the intended purpose of the R&D expenditures in our analysis: 'Physical-R&D', which includes natural sciences and engineering R&D expenditures; and 'Social-R&D', which includes social sciences, humanities and the arts R&D expenditures. To clarify, total 'R&D' is the sum of both 'Physical-R&D' and 'Social-R&D'. The purpose of decomposing R&D expenditures into 'Physical-R&D' and 'Social-R&D' is to capture whether one form of R&D expenditures has a more significant effect on pollution outcomes at the level of an industrial facility. We hypothesize that 'Physical-R&D' would have a more significant emissions effect on industrial facilities due to the capital-intensive nature of industrial operations. We do not draw the same hypothesis for 'Social-R&D'. In summary, we test three R&D variables in our analysis: 'R&D' (total R&D); 'Physical-R&D' (natural sciences and engineering R&D); and 'Social-R&D' (social sciences, humanities and the arts R&D). All three R&D variables, as well as all economic variables listed below, were collected for all 10 Canadian provinces: Newfoundland, Prince Edward Island, Nova Scotia, New Brunswick, Quebec, Ontario, Manitoba, Saskatchewan, Alberta, and British Columba.

In addition to the facility CO_2eq. emissions dataset and R&D variables, this study also utilizes annual provincial data from CANSIM (Canadian Socio-Economic Information Management System), accessed through Statistics Canada. We collected annual provincial variables for the years of 2004-2016, which include: 'GDPPC' gross domestic product per capita (equal to provincial gross domestic product at market prices [chained 2012, $ x 1,000,000] divided by provincial population) ; 'INCOMEPC' real gross domestic income per capita (chained 2002 $, divided by provincial population); 'TRADE-open' international trade openness (equal to provincial international exports and imports to other countries [$ x 1,000,000] divided by provincial GDP [chained 2012, $ x 1,000,000]); 'POPD' annual population density (equal to provincial population estimates on July 1st divided by provincial land area in square kilometres); 'EDU-employ' proportion of provincial workforce (persons, age 15 and older) working in educational services and lastly, 'POLLAB' expenditures on pollution abatement and control processes (end-of-pipe) by sector ($ x 1,000,000).[1]

Due to data availability, some variables were also collected at the sectoral level. The inclusion of sectors is based on the North American Industry Classification System (NAICS). The sectoral variables included in our study are matched based on NAICS codes reported by facilities in the pollution dataset. Five sectors were included in the dataset including: Mining and Oil and Gas Extraction [21]; Utilities [22]; Manufacturing [31-33]; Transportation and Warehousing [48-49]; and Administrative and Support, Waste Management and Remediation Services [56]. Sectoral-level variables collected from Statistics Canada for the period of 2004-2016, include: 'FDI' foreign direct investment in Canada (annual, $ x 1,000,000); and 'KL'

[1] We note that this measure of pollution abatement expenditures came from two separate biannual data tables to allow this proxy to match the panel time period. We took the average value between biannual values of pollution abatement by province. We are careful in our interpretation of this variable in the results.

capital-labour ratio (equal to investment in fixed non-residential capital [chained 2012, $ x 1,000,000] divided by labour [total number of jobs, by sector and province]).

Chapter 4: Empirical Analysis

4.0 Empirical Model

To examine the effect of technological change on environmental performance of industrial firms, we specify a spatial-dynamic model of emissions:

$$\boldsymbol{y}_{i,t} = \varphi \boldsymbol{y}_{i,t-1} + \rho \boldsymbol{W} \boldsymbol{y}_{i,t} + \boldsymbol{X}_{i,t} \boldsymbol{\beta} + \boldsymbol{\lambda}_i + \boldsymbol{\gamma}_t + \boldsymbol{\xi}_{i,t} \qquad \text{(Eq. 3)}$$

where $\boldsymbol{y}_{i,t}$ and $\boldsymbol{y}_{i,t-1}$ denote n×1 vectors of current and lagged CO_2eq. emissions of industrial firms at time t = 2004 … 2016 (operating in in sector s and province r). $\boldsymbol{W}$ is a n×n, row-standardized spatial weight matrix based on the geographical proximity in square kilometers from latitude and longitude coordinates of each firm. $\boldsymbol{X}_{i,t}$ denotes a n×k matrix of time varying explanatory variables at the sectoral and provincial levels with corresponding coefficient vector $\boldsymbol{\beta}$. The vectors, $\boldsymbol{\lambda}_i$ and $\boldsymbol{\gamma}_t$, denote firm and time fixed effects that capture unobserved heterogeneity in emissions across firms and common covariate time-specific shocks, respectively. Finally, $\boldsymbol{\xi}_t$ is a n×1 vector of idiosyncratic shocks, that captures unobserved effects on $\boldsymbol{y}_t$, and is assumed to be normally distributed, zero-mean, homoskedastic and serially uncorrelated within and across firms.

The coefficient, φ, on lagged emissions captures persistence in emission levels through time, and controls, in reduced form, for the effect of facility-specific time-varying factors that could influence emissions. Many studies fail to account for the dynamic considerations of emissions, through which industrial pollution tends to persist through time. If φ is positive, then this result provides support for the hypothesis that firm pollution accumulates in the long run. If φ is negative, then this result provides support for the hypothesis that firm pollution diminishes in the long run. If φ is insignificant, then there is no evidence to suggest either hypothesis is occurring.

The coefficient, ρ, captures the effect of spatial spillovers of pollution between firms. ρ allows us to directly test the hypothesis of spatial-spillovers in pollution, due to net and possibly complimentary effects of: location-specific regulation, industry agglomeration, 'best practices' of pollution control passed between firms, and 'yardstick competition' between firms to gain social license. If ρ is positive, then there is evidence to support the hypothesis that there are complimentary positive spatial effects between firms; therefore, a facility surrounded by high-polluting facilities is significantly more likely to exhibit high-polluting behaviors, and vice versa for low-polluting firms. If instead, ρ is negative, then there is evidence to suggest that a facility surrounded by high-polluting facilities is significantly more likely to exhibit low-polluting behaviors, and vice versa for low-polluting firms. There are no theories that suggest a negative spatial-spillover trend is likely to occur between industrial emitters. If ρ is insignificant, then there is no evidence to suggest either spatial spillovers of pollution effect is occurring.

We include in $\boldsymbol{X}_{i,t}$ a series of covariates based on our literature review in the previous section (discussed in detail in the upcoming subsection). Our control variables in $\boldsymbol{X}_{i,t}$ include both provincial and sectoral variables. We do not include firm-level variables, such as firm-level R&D expenditures or employment, given limited data availability and to avoid obvious endogeneity issues associated with their inclusion.

Estimation of equation 3 presents two distinct challenges. First, ignoring the spatial terms, the presence of the lagged dependent variable, $\boldsymbol{y}_{i,t-1}$, in the panel data model creates an endogeneity problem. Equation 3 cannot be estimated by pooled OLS or generalized least squares since the errors and individual unobserved heterogeneity ($\boldsymbol{\lambda}_i$) will be correlated with the lagged dependent variable. Fixed effects estimation is also inconsistent given the finite time dimension (Hsiao, 2007). A solution prosed by Arellano and Bond (1991) is to use differencing together with instrumental variable methods. The consistent generalized method of moments (GMM) estimator used under this approach uses lags of the level or differences of emissions as instruments for the lagged emission variable after the firm and time fixed effects are removed by first-differencing.

A second challenge in estimating equation 3 is that, ignoring the dynamic lagged emission variable, the lagged spatial term, $\boldsymbol{W}\boldsymbol{y}_{i,t}$, is endogenous due to the reflection problem (Manski, 1993). The result of the reflection problem is not being able to disentangle two-way directional causality of the neighbor in relation to the individual ('I am my neighbor's neighbor'). Kelejian and Prucha (1998) propose a solution where the endogenous spatial lag term is instrumented using spatial lags of the exogenous explanatory variables as instruments. Following Kelejian and Prucha, we specify the $\boldsymbol{W}\boldsymbol{X}_{i,t}$ matrix as valid spatial instruments for our analysis. This form of instrumentation, combine with GMM estimation, simultaneously controls for the joint dependence of the $\boldsymbol{W}\boldsymbol{y}_{i,t}$ and $\boldsymbol{\xi}_{i,t}$ in each cross-section (Liu and Saraiva, 2015).

Finally, there is concern of instrument validity whereby the instruments need to be uncorrelated with the error term of equation 3. With an over-identified system, instrument validity can be tested using the Sargan test (Arellano and Bond, 1991). We use this approach to jointly test the validity of both the spatial and dynamic instrumental variables.

We follow Shehata, et al. (2012) who provide an integrated framework to overcome the above challenges by instrumenting for both the endogenous spatial lag and the endogenous lagged dependent variable, while differencing out the fixed effects (Davies and Vadlammanti, 2013). More specifically, we account for dynamic and spatial effects of facility emissions by using a Spatial Lag Dynamic Panel Data model (SDPD), which combines both spatial and dynamic lags and relies on GMM estimation. This approach also aligns with the work of Kukenova and Monteiro (2008), who suggests that the spatial lag dynamic panel data GMM estimator outperforms the spatial maximum likelihood estimator (MLE); spatial dynamic MLE (Elhorst, 2005); and spatial dynamic quasi-MLE (Yu et al., 2008), in terms of bias, root mean squared error and standard-error accuracy. Overall, through this integrated approach SDPD allows us to instrument the endogenous lagged and spatially-lagged dependent variable, as well as control for the presence of measurement errors (Madariaga and Ponce, 2007).

4.1 Specification and Expected Signs

The descriptive statistics and expected signs of all variables are presented in Table 1 below. For all models, the dependent variable, facility emissions, as well as the lag and spatial-lag covariates and the main variables of interest: R&D, Physical-R&D and Social-R&D, are expressed in logarithmic form. All other explanatory variables are expressed in linear form for the analysis.

Table 1. Summary of descriptive statistics, predicted signs and variable definitions.[2]

Variable	*Mean*	*St. Dev.*	*Min*	*Max*	*Pred. sign*[3]	*Definition*
Lag-Emissions	892,644	1,676,330	6379	1.64e+07	+	Ln (One year temporal lag of facility GHG emissions, T-1)
Spatial-lag emissions	921,985	1,259,868	10,989	1.56e+07	+	Ln (Inverse Km^2 geographical proximity spatial-lag of facility GHG emissions)
R&D	5,608.8	4,890.245	46	14,490	-	Ln (Total provincial R&D expenditures, T-1)
Physical-R&D	5160.2	4503.408	38	13559	-	Ln (Total provincial ‘physical-science’ R&D expenditures, T-1)
Social-R&D	448.66	403.19	7.0	1369	-	Ln (Total provincial ‘social-science’ R&D expenditures, T-1)
GDPPC	0.4743	0.1936	0.2089	0.7786	+	Provincial GDP per capita
KL	5.668	50.66	0.00002	664.1	+	Sectoral capital-labour ratio
POLLAB	201.96	213.08	0.9818	1276	-	Provincial pollution abatement expenditures
INCOME PC	54,462	13,965.0	31,626.2	80,031.8	-	Provincial gross domestic income per capita
TRADE-open	0.6030	0.1037	0.3799	1.098	+/-	Provincial international-trade openness = (Provincial EX + IM)/ Provincial GDP
EDU-employ	0.0695	0.0075	0.0583	0.1038	+/-	Provincial proportion of labour force in educational services
FDI	108234.5	74832.13	569.8333	198820	-	Sectoral foreign direct investment
POPD	7.775038	4.691518	1.373872	26.28759	+/-	Provincial population density, persons per sq. km

[2] The ‘Mean’ value for the above explanatory variables reflects the average value of the variable for all facilities represented in our dataset. For example, the ‘true mean’ of R&D expenditures across all provinces in Canada is $2.5 billion annually. Whereas in our dataset, there is a higher proportion of facilities located in high R&D spending provinces, therefore across all facilities the ‘average R&D’ facilities face is $5.6 Billion.
[3] Predicted sign of coefficient estimate.

R&D captures provincial technological change, and is our main indicator of the technique effect. The coefficient on this variable allows us to directly test the marginal effect of technological change on industrial firm emissions, while accounting for both spatial and dynamic properties of pollution and two-way fixed effects. If the coefficient on R&D is negative, then there is evidence to support the hypothesis that increased technological expenditures have a net negative effect on industrial firm emissions; therefore, a facility in a province with higher technological investment is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a province with low-technology investment, on average. If instead, the coefficient on R&D is positive, then there is evidence to suggest that a facility in a province with higher technological investment is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low-technology investment, on average. If the coefficient on R&D is insignificant, then there is no evidence to suggest either firm-level pollution behavior is occurring.

The additional specifications of Physical-R&D and Social-R&D allow us to test the individual effects of different types of R&D on industrial facility emissions. More specifically it allows us to test whether Physical-R&D has a more significant emissions effect compared to Social-R&D, hypothesized due to the capital-intensive nature of industrial emissions. If the coefficient on Physical-R&D [Social-R&D] is negative, then there is evidence to support the hypothesis that increased provincial technological expenditures in natural sciences and engineering [social sciences, humanities, and the arts] have a net negative effect on industrial firm emissions; therefore, a facility in a province with higher technological investment in Physical-R&D [Social-R&D] is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a province with low-technology investment in Physical-R&D

[Social-R&D], on average. If instead, the coefficient on Physical-R&D [Social-R&D] is positive, then there is evidence to suggest that a facility in a province with higher technological investment in natural sciences and engineering [social sciences, humanities, and the arts] is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low-technology investment in Physical-R&D [Social-R&D], on average. If the coefficients on Physical-R&D and Social-R&D are insignificant, then there is no evidence to suggest either firm-level pollution behavior is occurring.

Our measure of the scale effect is GDPPC, which captures the increase in pollution as a result of an expansion of economic activity in a province, scaled by population. The inclusion of this variable allows us to control for provincial economic fluctuations and test the extent to which firm-level pollution outcomes are driven solely by expansions in economic activity. If the coefficient on GDPPC is positive, then there is evidence to support the hypothesis that increasing provincial economic activity is directly linked to increases in industrial firm emissions; therefore, a facility in a province with high GDPPC is significantly more likely to exhibit higher-pollution behaviors, compared to a facility in a province with low GDPPC, on average. If instead, the coefficient on GDPPC is negative, then there is evidence to suggest that a facility in a province with high GDPPC is significantly more likely to exhibit emission reductions behaviors, compared to a facility in a province with low GDPPC, on average. If the coefficient on GDPPC is insignificant, then there is no evidence to suggest either firm-level pollution behavior is determined by differences in provincial economic output.

Our measure of the composition effect is KL, which captures the ratio of capital-to-labour inputs in total production by sector. The inclusion of this variable allows us to control for sectoral differences in capital and labour inputs, as well as test the hypothesis that firms with higher ratios of capital-to-labour inputs are more pollution intensive. If the coefficient on KL is positive, then there is evidence to support the hypothesis that higher levels of sectoral capital inputs (compared to labour) is directly linked to increases in industrial firm emissions; therefore, a facility in a sector with high KL is significantly more likely to exhibit higher-pollution behaviors, compared to a facility in a sector with low KL, on average. If instead, the coefficient on KL is negative, then there is evidence to suggest that a facility in a sector with high KL is significantly more likely to exhibit emission reductions behaviors, compared to a facility in a sector with low KL, on average. If the coefficient on KL is insignificant, then there is no evidence to suggest either firm-level pollution behavior is determined by differences in sectoral input levels.

We include two alternative technique effect measures, motivated by the economic growth-environment literature, POLLAB and INCOMEPC. POLLAB captures 'end-of-pipe' expenditures on pollution abatement by province and proxies provincial environmental regulation stringency. The inclusion of this variable allows us to control for estimated provincial stringency differences in environmental regulation, as well as test the hypothesis that firms in provinces with higher 'end-of-pipe' pollution control expenditures results in lower industrial emissions, on average. If the coefficient on POLLAB is negative, then there is evidence to support the hypothesis that higher levels of provincial pollution abatement expenditures is directly linked to decreases in industrial firm emissions; therefore, a facility in a province with high environmental regulation stringency is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a province with low environmental regulation stringency, on average. If instead, the coefficient on POLLAB is positive, then there is evidence to suggest that a facility in a province with high environmental regulation stringency is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low environmental regulation stringency, on average. If the coefficient on POLLAB is insignificant, then there is no evidence to suggest either firm-level pollution behavior is occurring.

INCOMEPC captures the decrease in pollution as a result of an increase in real provincial income, scaled by population. The inclusion of this variable allows us to control for provincial differences in real income levels; as well as test the hypothesis that higher incomes are correlated with higher living standards and a higher preference for environment quality. If the coefficient on INCOMEPC is negative, then there is evidence to support the hypothesis that higher levels of provincial INCOMEPC is directly linked to decreases in industrial firm emissions; therefore, a facility in a province with high INCOMEPC is significantly more likely to exhibit pollution reduction behaviors, compared to a facility in a province with low INCOMEPC, on average. If instead, the coefficient on INCOMEPC is positive, then there is evidence to suggest that a facility in a province with high INCOMEPC is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low INCOMEPC, on average. If the coefficient on INCOMEPC is insignificant, then there is no evidence to suggest either firm-level pollution behavior is occurring.

Motivated by the economic growth environment literature, four additional pollution determinants are included in our empirical specification: TRADE-open; EDU-employ; FDI; and POPD. TRADE-open captures the pollution effect associated with an expansion of net international trade flows by provinces, scaled by provincial GDP. The inclusion of this variable allows us to account for the net flow of goods and services in and out of a province; and test the extent to which firm-level pollution outcomes are driven solely by expansions in international trade activity. If the coefficient on TRADE-open is positive, then there is evidence to support the hypothesis that increasing provincial trade activity is directly linked to increases in industrial firm emissions; therefore, a facility in a province with a high trade-openness is significantly more likely to exhibit higher-pollution behaviors, compared to a facility in a province with a low trade-openness, on average. If instead, the coefficient on TRADE-open is negative, then there is evidence to suggest that a facility in a province with a high trade-openness is significantly more likely to exhibit emission-reductions behaviors, compared to a facility in a province with a low trade-openness, on average. If the coefficient on TRADE-open is insignificant, then there is no evidence to suggest either firm-level pollution behavior is determined by differences in international trade flows by Canadian provinces.

EDU-employ is a direct measure of education levels in a region, scaled by population. The inclusion of this variable allows us to control for provincial differences in knowledge accumulation; and test the hypothesis that higher levels of knowledge accumulation encourages facilities, through a learning-by-doing process, to implement the most effective pollution-reduction technologies and reduce compliance costs in the long run. If the coefficient on EDU-employ is negative, then there is evidence to support the hypothesis that higher levels of provincial knowledge accumulation is directly linked to decreases in industrial firm emissions; therefore, a facility in a province with high EDU-employ is significantly more likely to exhibit pollution reduction behaviors, compared to a facility in a province with low EDU-employ, on average. If instead, the coefficient on EDU-employ is positive, then there is evidence to suggest that a facility in a province with high EDU-employ is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low EDU-employ, on average. If the coefficient on EDU-employ is insignificant, then there is no evidence to suggest either firm-level pollution behavior is due to provincial differences in knowledge accumulation.

FDI captures foreign direct investment, by sector. The inclusion of this variable allows us to control for sectoral differences in international capital shocks that may influence pollution; as well as, test the hypothesis that sectors that receive increased access to financial resources, new technology and a skill-upgraded work force are less-pollution intensive. If the coefficient on FDI is negative, then there is evidence to support the hypothesis that higher levels of sectoral foreign direct investment is directly linked to decreases in industrial firm emissions; therefore, a facility in a sector with high FDI is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a sector with low FDI, on average. If instead, the coefficient on FDI is positive, then there is evidence to suggest that a facility in a sector with high FDI is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a sector with low FDI, on average. If the coefficient on FDI is insignificant, then there is no evidence to suggest either firm-level pollution behavior is determined by differences in sectoral-level foreign direct investment.

POPD, captures population density, scaled by provincial area in square kilometers. The inclusion of this variable allows us to proxy informal regulatory pressure, as greater lobbying pressure is often correlated with a larger number of people in a particular area. In addition, including POPD allows us to test the hypotheses that provinces with more people leads to: more concentrated pollution levels (+), or lower pollution levels due to a higher net benefit of pollution abatement (-). If the coefficient on POPD is negative, then there is evidence to support the hypothesis that higher provincial population densities are directly linked to decreases in industrial firm emissions; therefore, a facility in a province with high POPD is significantly more likely to exhibit pollution reduction behaviors, compared to a facility in a province with low POPD, on average. If instead, the coefficient on POPD is positive, then there is evidence to suggest that a facility in a province with high POPD is significantly more likely to exhibit high-polluting behaviors, compared to a facility in a province with low POPD, on average. If the coefficient on POPD is insignificant, then there is no evidence to suggest either firm-level pollution behavior is occurring due to differences in provincial population density.

Chapter 5: Results of Spatial Lag Dynamic Panel Data Model

5.0 Model Estimation

Our baseline specification, which is common across all models presented in this section, includes lagged-emissions, spatially-lagged emissions, the scale effect (GDPPC), the composition effect (KL), TRADE-openness, POLLAB, INCOMEPC, and one of the three categories of our main variable of interest: R&D, Physical-R&D, or Social-R&D. In total we present the results of nine spatial-dynamic model estimations. In models 1 to 3, we test the validity of our technique effect measure, R&D, by incorporating the alternative, empirically-motivated technique effect measures: pollution abatement expenditures, POLLAB, and income per capita, INCOMEPC. In models 5 and 6 we decompose the science-categories of R&D into Physical-R&D and Social-R&D, respectively. To test the sensitivity of our results with the inclusion of other empirically-supported pollution determinants, we estimate three additional specifications that independently introduce the following control variables: EDU-employ; FDI; and POPD (models 7, 8 and 9, respectively). Across all models, technological change, measured through provincial R&D expenditures, has a significant and negative impact on facility emissions.

The Sargan Test is used to ensure that both the spatial and dynamic instruments are valid. In all models iterated, we fail to reject the null hypotheses that the instruments are valid (results are presented in Table 2 below). Based on the quite stable adjusted R-squared values across all models, we assert that our models have a high goodness-of-fit and that the percentage of explained variation in the dependent variable, emissions, is not simply due to adding more explanatory variables to the estimation. Based on a Wald Test across all models, we reject the null hypothesis that the estimated coefficients are simultaneously equal to zero. This suggests that removing explanatory variables from the estimation will harm the fit of our model. The Fstatistic and Log-likelihood Test additionally confirm the significance of our coefficient estimates.

Table 2 presents the results of the Spatial Lag Dynamic Panel Data GMM estimator. Interestingly, the results are highly consistent with most of our expected signs on coefficients in all our models, as outlined by Table 1 in the empirical section. This finding provides additional support for the overall fit of the model

Table 2. Summary of Spatial Lag Dynamic Panel Data Regression (N = 2700)
Note: ***p < 0.01; **p < 0.05; *p < 0.10; Values in brackets are t-statistics

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	8	9
φ (Lag-emissions)	0.391***	0.345***	0.391***	0.342***	0.343***	0.325***	0.345***	0.342***	0.355***
	(19.20)	(17.52)	(19.44)	(17.51)	(17.45)	(15.83)	(17.58)	(18.32)	(17.45)
ρ (Spatial-lag emissions)	0.216***	0.108***	0.192***	0.090**	0.092**	0.099***	0.097***	0.091**	0.092**
	(5.09)	(2.90)	(4.50)	(2.40)	(2.43)	(2.57)	(2.73)	(2.43)	(2.37)
GDPPC	0.288**	1.02***	0.506***	1.198***	1.234***	1.441***	1.009***	1.185***	1.184***
	(2.37)	(5.24)	(3.63)	(5.79)	(6.00)	(5.87)	(4.65)	(5.75)	(4.31)
KL	0.0003	0.0001	0.0004	0.0003	0.0003	0.0005	0.0003	0.0002	0.0005
	(0.44)	(0.20)	(0.71)	(0.41)	(0.39)	(0.73)	(0.41)	(0.24)	(0.71)
TRADE-open	0.565***	0.787***	0.540***	0.756***	0.759***	0.734***	0.701***	0.746***	0.741***
	(6.01)	(7.95)	(5.67)	(7.56)	(7.57)	(7.35)	(6.80)	(7.49)	(7.35)
POLLAB			4.74e-4***	3.40e-5**	3.42e-5**	4.79e-5***	3.12e-5**	3.10e-5**	3.39e-5**
			(2.57)	(2.30)	(2.35)	(3.31)	(2.18)	(2.10)	(2.21)
INCOMEPC		-5.01e-6***		-4.92e-6***	-5.08e-6***	-5.74e-6***	-4.51e-6***	-4.78e-6***	-4.81e-6***
		(-5.07)		(-4.91)	(-5.10)	(-4.96)	(-4.58)	(-4.77)	(-3.97)
constant	5.862***	7.41***	5.761***	7.362***	7.344***	6.512***	7.60***	7.41***	7.18***
	(8.24)	(11.52)	(8.10)	(11.39)	(11.62)	(10.79)	(11.64)	(11.75)	(10.73)
R&D	-0.151***	-0.122***	-0.113***	-0.093**			-0.100**	-0.097**	-0.092**
	(-3.76)	(-3.10)	(-2.64)	(-2.17)			(-2.35)	(-2.30)	(-2.13)
Physical-R&D					-0.096**				
					(-2.38)				
Social R&D						0.028			
						(0.91)			
EDU-employ							-2.72		
							(-1.56)		
FDI								-7.85e-8	
								(-0.88)	
POPD									-0.0004
									(-0.02)
Adj R-sq	0.162	0.147	0.169	0.151	0.154	0.148	0.151	0.161	0.156
Wald Test	526.75	470.74	553.98	486.95	488.04	474.82	486.77	525.33	508.15
F-stat	87.79	67.25	79.14	60.8	61.01	59.35	54.09	58.37	56.46
Log likelihood	283.33	229.45	287.89	227.38	227.02	199.41	232.63	225.50	246.54
Sargan LM	0.127	0.290	0.153	0.286	0.301	0.257	0.225	0.298	0.281

5.1 Results

The coefficient estimate on lagged emissions, φ, which captures persistence in emission levels through time, is positive and significant across all models. The magnitude of the coefficient is less than unity signaling a stationary process of the evolution of emissions over time. The positive coefficient suggests that a 1% increase in a facility's average previous-year CO_2eq. emissions results in a 0.325% to 0.391% increase in present day CO_2eq. emissions, ceteris paribus. Or, a 10% increase in a facility's previous-year CO_2eq. emissions results in 3.25% to 3.91% increase in present day CO_2eq. emissions, on average. This result provides support for the hypothesis that firm pollution accumulates in the long run. We conclude that there is systematic temporal-persistence between historical and current pollution levels for industrial facilities in Canada, on average. This result, indicating that lagged-emissions is a significant determinant of industrial pollution, is consistent with the literature on the dynamic effects of economic growth and pollution. This temporal-persistence in emissions is justified by several theories, such as: technological path-dependency (disincentive associated with high costs of switching to more environmentally-friendly technological regimes); or, economies of scale (incentive for facilities to maximize profits and recuperate high start-up costs through increased production).

The coefficient estimate on spatially-lagged emissions, ρ, which captures the effect of spatial spillovers of pollution between firms, is positive and significant across all models. The positive coefficient on spatially-lagged emissions suggests that a 1% increase in neighborhood average CO_2eq. emissions results in a 0.090% to 0.216% increase in own-facility CO_2eq. emissions, ceteris paribus. Or, a 10% increase in neighborhood CO_2eq. emissions results in 0.90% to 2.16% increase in own-facility CO_2eq. emissions, on average. Since ρ is positive, we conclude that a facility surrounded by high-polluting facilities is significantly more likely to exhibit high-polluting behaviors, and vice versa for low-polluting firms. This finding is consistent with the spatial spillovers of pollution literature and reveals a positive complimentary emissions effect for firms in close geographical-proximity. This finding reveals the extent to which facility emissions are influenced by the emissions of neighboring facilities and confirms the significance of including a spatially lagged dependent variable in the empirical analysis of industrial pollution. Further analysis is required to deduce whether this spatial-spillover of emissions effect is associated with individual or complimentary theories, such as: location-specific regulation, industry agglomeration, 'best practices' of pollution control passed between firms, and 'yardstick competition' between firms to gain social license.

The coefficient estimate on our technique effect measure, R&D, which captures the marginal effect of technological change on industrial firm emissions, is negative and significant across all models. This estimate allows us to address the main objective of this thesis. The negative coefficient on R&D suggests that a 1% increase in R&D spending at the level of the province results on average in a 0.092% to 0.151% decrease in CO_2eq. emissions at the level of the facility. Assuming average facility emissions and R&D levels, we find that a provincial R&D shock of $56 million (a 1% increase in average provincial R&D expenditures for facilities in our sample), would result in a CO_2eq. emissions reduction of 0.82-1.35 kilotonnes (kt) per facility (0.092% to 0.151% decrease in facility CO_2eq. emissions), on average. As the average industrial CO_2eq. emissions for an individual facility is approximately 893 kt for our sample, we conclude that the overall emissions impact of technological change, measured through R&D expenditures, is relatively small. An alternative interpretation of this result is that the average total cost of R&D per unit of CO_2eq. reduction is $185/tonne to $304/tonne. This result suggests that the cost of emissions reduction technology is considerably higher than the $30/tonne regulatory price on CO_2eq. emissions currently in place in Canada.

Although the emissions effect of R&D is relatively small in proportion, our results provide evidence to support the hypothesis that increased technological expenditures have a net negative effect on industrial firm emissions; and that a facility in a province with higher technological investment is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a province with low-technology investment, on average. This finding aligns with the theory contributed by the technological change-environment literature. In addition, this finding is consistent with the economic growth-environment literature led by Copeland and Taylor (2004), which posits that the technique effect reduces the emissions-intensity of production, often due to a substitution of dirty and inefficient technology for more sophisticated and cleaner methods. Further analysis is required to deduce the mechanisms through which technological change permeates into industrial facilities and thereby, reduces emissions, on average. Preliminary insights surrounding the relationship between technology and industrial facilities in Canada are presented in the conclusion section of this thesis, with the aim of inspiring future inquiry.

The additional specifications of Physical-R&D and Social-R&D are added in models 5 and 6, to test the individual effects of different types of R&D on industrial facility emissions. The coefficient estimate for Physical-R&D is negative and significant, whereas the coefficient estimate on Social-R&D is insignificant across our estimations. As for the first finding, it appears that a 1% increase in provincial technological expenditures in natural sciences and engineering results on average, results in a 0.096% decrease in facility CO_2eq. emissions, ceteris paribus. Or, a 10% increase in Physical-R&D results in 0.96% reduction in facility CO_2eq. emissions, on average. This provides evidence to support the hypothesis that increased provincial technological expenditures in natural sciences and engineering has a net negative effect on industrial firm emissions and that a facility in a province with higher technological investment in Physical-R&D is significantly more likely to exhibit pollution-reduction behaviors, compared to a facility in a province with low-technology investment in Physical-R&D, on average. As the coefficient on Social-R&D is insignificant, there is no evidence to suggest firm-level industrial pollution behavior is influenced by higher provincial technological investment in social sciences, humanities, and the arts. We conclude that there is a high probability that the negative, significant 'total' R&D emissions effect we observe, is primarily due to the role of provincial technological expenditures in natural sciences and engineering. This aligns with our original hypothesis that Physical-R&D would have a more significant emissions effect compared to Social-R&D, due to the capital-intensive characteristics of industrial operations. We conclude that, on average, higher provincial technological investment in natural sciences and engineering may be a key mechanism through which technological change permeates into industrial markets and translates into firm-level environmental performance outcomes in Canada.

The coefficient estimate on the scale effect measure, GDPPC, which captures increases in pollution as a result of provincial expansions of economic activity per capita, is positive and significant across all models. The positive coefficient on GDPPC suggests that on average, a 1 unit increase in gross domestic product per capita (1 unit= \$1,000,000/person) results in a 22.8% to 144.1% increase in CO_2eq. emissions at the level of the facility, ceteris paribus. Since GDPPC is positive, there is evidence to support the hypothesis that increasing provincial economic activity is directly linked to increases in industrial firm emissions; therefore, a facility in a province with high GDPPC is significantly more likely to exhibit higher-pollution behaviors, compared to a facility in a province with low GDPPC, on average. This finding is consistent with the economic growth-environment literature led by Copeland and Taylor (2004), which posits that the scale effect is expected to increase pollution response.

The net effect on pollution can be gleaned by comparing the magnitude of the estimated emissions impact of the scale effect measure, GDPPC, and the technique effect measure, R&D. Table 3, below, outlines the effect of a R&D and GDP shock of the same magnitude in detail. Using the mean values for: facility emissions; provincial R&D expenditures; provincial GDPPC; and provincial population values, we compare the emissions effect of an economic shock from R&D and GDP of the same magnitude. Our results show that the scale effect largely dominates the technique effect (measured through technological change) across all models. Assuming a status-quo R&D expenditure of 1.39% of provincial GDP, in conjunction with 1.39% increase in provincial GDP, we predict the combined result of the scale and technique effects is a net, positive increase in facility CO_2eq. emissions of 2.76 to 16.58 kt, per facility. Cumulatively, this result means that for all 225 firms we analyzed, a R&D shock reduces emissions 184 kt to 303 kt; while a GDP-growth shock of the same magnitude increases CO_2eq. emissions by 806 kt to 4,034 kt. The net outcome of these two effects is an additional 622 kt to 3,930 kt of CO_2eq. emissions entering the atmosphere from a subset of 225 industrial facilities in Canada. This result is significant as it suggests that, on average, the current rate of technological advancement will reduce industrial CO_2eq. emissions at a rate slower than the emissions growth associated with increases in economic activity.

Table 3. Estimated emissions effect of provincial R&D and provincial GDP shocks, both at 1.39% of average provincial GDP expenditures.

	Per Facility Change in CO_2eq. Emissions[4]		225 Facility Change in CO_2eq. Emissions[5]	
	Low Case	**High Case**	**Low Case**	**High Case**
Technique effect[6] (R&D shock of 1.39% provincial GDP)	- 0.82 kt	- 1.35 kt	- 184.5 kt	- 303.1 kt
Scale effect[7] (GDP shock of 1.39% average provincial GDP)	+ 3.58 kt	+ 17.93 kt	+ 806.3 kt	+ 4,034 kt
Net effects[8] (sum of both technique and scale effects)	**+ 2.76 kt**	**+ 16.58 kt**	**+ 621.8 kt**	**+ 3,930 kt**

4 All units reflect kilotonnes of carbon dioxide equivalent emissions from facilities.
5 '225 Facility Change in CO_2eq. Emissions' values do not exactly equal 'Per Facility Change in CO_2eq. Emissions' times 225, as aggregate calculations were completed prior to rounding.
6 Results were calculated assuming mean provincial R&D expenditures of $5,608.861 ($, million) and mean facility emissions of 892,644.3 tonnes of carbon dioxide equivalent emissions per facility.
7 Results were calculated assuming a mean provincial gross domestic product per capita value of 0.4743 ($, million/person), mean provincial population of 848,248 persons per province, and mean facility emissions of 892,644.3 tonnes of carbon dioxide equivalent emissions per facility. The ratio of annual, mean provincial R&D expenditures to provincial GDP expenditures is 0.013939. Thus, a rate of 1.39% is assumed for both estimated R&D and GDP shocks.
8 Only the scale and technique effects were compared as the coefficient estimate on the composition effect is insignificant across all models.

The control variables in our model mostly have expected theoretical signs. The coefficient estimate on the composition effect measure, KL, which captures the ratio of sectoral capital-to-labour inputs in total production, is positive, yet insignificant across all models. Although the inclusion of this variable is still valuable as it allows us to control for sectoral differences in capital and labour inputs, we are not able to test the hypothesis that firms with higher ratios of capital-to-labour inputs are more pollution intensive. Since the coefficient on KL is insignificant, there is no evidence to suggest firm-level pollution behavior is determined by differences in sectoral capital and labour input levels.

Across all models, we obtain a significant coefficient estimate for our first alternative technique effect measure, POLLAB. The significant coefficient estimate on POLLAB suggests that on average, a 1 unit increase in provincial pollution abatement expenditures (1 unit= $1,000,000) results, on average, in a 0.0031% to 0.0474% change in CO_2eq. emissions at the level of the facility, ceteris paribus. We remind the reader that the proxy of pollution abatement expenditures came from two separate biannual data tables to allow this proxy to match the panel time series. Thus, we are careful with our interpretation of this result. We conclude that expenditures on 'end-of-pipe' pollution abatement by province has a small marginal effect on industrial firm emissions. We suggest, however, that further inquiry into this result be undertaken if annual panel data on 'end-of-pipe' pollution abatement expenditures becomes available in the future.

Across all models, we obtain a significant coefficient estimate for our second alternative technique effect measure, INCOMEPC. The inclusion of this variable is valuable as it allows us to control for provincial differences in real income per capita and test the hypothesis that provinces with higher real incomes per capita are correlated with higher preferences for environmental quality and lower pollution intensive industrial activity. The significant coefficient estimate on INCOMEPC suggests that on average, a 1 unit increase in real income per capita (1 unit= $/person) results, on average, in a 0.000451% to 0.000574% decrease in CO_2eq. emissions at the level of the facility, ceteris paribus. We conclude that provincial real income per capita (1 unit= $/person) has a small marginal effect on industrial firm emissions.

We test the significance of including additional technique effect measures, POLLAB and INCOMEPC, in models 1 to 3. We observe a very small dampening effect on the coefficient of R&D with the inclusion of either the POLLAB or INCOMEPC covariates. We conclude that the inclusion of these alternative technique effects does not have a significant impact on the sign or magnitude of the coefficient estimate on our main variable of interest, R&D.

The coefficient estimate on provincial trade-openness, TRADE-open, which captures increases in pollution as a result of provincial expansions of trade activity scaled by GDP, is positive and significant across all models. The positive coefficient estimate on TRADE-open suggests that on average, a 1 unit increase in trade openness (ratio of international imports and exports/provincial GDP) results on average in a 54.0% to 78.7% increase in CO_2eq. emissions at the level of the facility, ceteris paribus. Since the coefficient on TRADE-open is positive, there is evidence to support the hypothesis that increasing provincial trade activity is directly linked to increases in industrial firm emissions; therefore, a facility in a province with a high trade-openness is significantly more likely to exhibit higher-pollution behaviors, compared to a facility in a province with a low trade-openness, on average. This finding is consistent with some studies in the international trade-environment literature, which posits that the scale effect of trade intensity can lead to an increase in pollution response.

We obtained negative and insignificant coefficient estimates for our final three determinants of pollution, included in our empirical specification: EDU-employ; FDI; and POPD. Since the coefficient estimate on EDU-employ is insignificant, we conclude there is no evidence to suggest that changes in average, industrial firm-level pollution behavior is due to provincial differences in knowledge accumulation. We suggest that additional proxies of knowledge accumulation could be pursued in future inquiry of this result. Due to the insignificant coefficient estimate on FDI, we conclude that there is no evidence to suggest that average, industrial firm-level pollution behavior is determined by differences in sectoral-level foreign direct investment. Finally, as the coefficient estimate on POPD is insignificant, there is no evidence to suggest average, industrial firm-level pollution behavior is significantly influenced by differences in provincial population density.

5.2 Robustness Check

We note that clustered standard errors may be a limitation of the results obtained for the spatially-lagged emissions coefficient estimate presented in Table 2. In particular, spatial correlation of the error terms may exist due to correlation within a cluster (i.e. facilities that belong to the same province may have correlated emissions performance). Spatial correlation of the error terms violates the assumption that facilities are independent within the same cluster (i.e. the same province) and would result in biased coefficient estimates (Sarzosa, 2012). This could occur if facilities within the same province have more similar emissions performance compared to facilities not within the same province, potentially due to correlated unobservable factors (e.g. provincial industrial type or industrial size). Further, the possibility of clustered standard errors would violate the assumption that $\boldsymbol{\xi}_t$, the vector of idiosyncratic shocks, is normally distributed, zero-mean, homoskedastic and serially uncorrelated within and across firms.

We test for spatial correlation of the standard errors by estimating the spatial lag dynamic panel data regression and applying a cluster estimation method that clusters standard errors by province. The estimation procedure fails to converge, therefore as an additional robustness check we create a provincial geographically-weighted spatial weight matrix (inverse geographical proximity in kilometres) that only assigns the spatial weighting if a pair of facilities belong to the same province. We then use matrix multiplication to create a spatially weighted emissions variable that tests the effect of spatial spillovers of pollution between firms within the same province (cluster). The results of the re-estimation are presented in Table 4 below. We note that we obtain all the same signs and relative magnitudes for all explanatory variables in the model compared to our estimation results in Table 2. This robustness check is consistent with our initial results, as we obtain a positive and significant coefficient on spatially-lagged emissions. Since ρ is positive after the re-estimation procedure, we conclude that a facility surrounded by high-polluting facilities is significantly more likely to exhibit high-polluting behaviors, and vice versa for low-polluting firms.

Table 4. Spatial Correlation of Standard Errors Estimation: Summary of Spatial Lag Dynamic Panel Data Regression (N = 2700)

Note: ***p < 0.01; **p < 0.05; *p < 0.10; Values in brackets are t-statistics

Variable	*1*
φ (Lag- emissions)	0.343*** (17.51)
ρ (Spatial-lag emissions, weighted by provincial dummy variables)	0.090** (2.40)
GDPPC	1.198*** (5.79)
KL	0.0003 (0.41)
TRADE-open	0.756*** (7.56)
POLLAB	3.40e-5** (2.30)
INCOMEPC	-4.92e-6***(-4.91)
constant	7.362*** (11.39)
R&D	-0.093** (-2.17)
Adj R-sq	0.151
Wald Test	486.95
Sargan LM	0.286

Chapter 6: Conclusion

6.0 Summary of Key Findings

Our study sought to econometrically estimate the impact of technological change, measured through provincial R&D expenditures in Canada, on pollution by Canadian firms. Additionally, our study aimed to provide insight into the mechanism through which technological change influences industrial pollution outcomes by decomposing R&D expenditures into scientific categories (physical and social sciences). Finally, our study sought to estimate the dynamic and spatial spillover effects of pollution and provide insight into the dynamic and spatial linkages that influence a firm's pollution decisions.

With regards to our main objective, to estimate the impact of technological change on pollution outcomes, we find that technological change, as predicted, had a negative and significant impact on average industrial facility emissions. In all nine models, we observe the expected signs for most of our control variables and find evidence to support a significant, negative emissions effect for our main variable of interest, R&D. We find that a provincial R&D shock of $56 million (a 1% increase in average provincial R&D expenditures for facilities in our sample), would result in an emissions reduction of 0.82 to 1.35 kt per facility (0.092% to 0.151% decrease in facility CO_2eq. emissions), on average. As the average industrial CO_2eq. emissions for an individual facility in our sample is approximately 893 kt, we conclude that the overall emissions impact of technological change, measured through R&D expenditures, is relatively small in magnitude. In addition, we find that the average total cost of R&D per unit of CO_2eq. reduction is $185/tonne to $304/tonne. We acknowledge that a potential limitation of our research is that our proxy, R&D, may not capture all technological change processes that result in emissions reductions at the level of a firm, thus resulting in an underreported value for the negative emissions effect of technological change. However, it is also plausible that the incentive structures that encourage industrial facilities to implement lower-emissions technology are weak or the costs to alter path-dependent technological regimes are still relatively high.

In our second objective, we decompose R&D expenditures into scientific categories (physical and social sciences), and find evidence to suggest that the significant, negative emissions effect associated with total R&D expenditures is predominately channeled through 'engineering and natural science' R&D. This result is not surprising as most of the sectors in our sample are highly capital-intensive and would rely heavily on technology upgrades in order to reduce emissions. Although, we did not find a significant industrial emissions effect from social-science R&D expenditures, further examination into the environmental outcomes associated this type of R&D may be useful for other emissions contexts in Canada (e.g. transportation sector; domestic electricity consumption, etc.). Our results suggest that in terms of industrial emissions, 'natural sciences and engineering' R&D investment is the most effective in achieving emissions reduction outcomes. Finally, we note that including only two categories of R&D funding may not capture the precise mechanism through which investment in technological change leads to industrial emissions reductions. Given more detailed data availability, we suggest that a further decomposition of R&D expenditures would be a valuable empirical exercise with significant implications for the Canadian literature on economic growth and the environment.

Following Copeland and Taylor's (2004) model of pollution, we analyzed the results of pollution supply (technological change, proxied through R&D expenditures) in relation to pollution demand (scale and composition effects). We find the composition effect to be insignificant across all models. However, as predicted by the economic growth-environment literature, we find a positive and significant coefficient estimate of the scale effect, measured through provincial GDP per capita. This suggests that expansions of economic activity in a province increase industrial pollution, ceteris paribus.

Similar to the results of a dynamic panel analysis conducted by Mohapatra et al. (2016), our results show that the scale effect largely dominates the technique effect (measured through technological change) across all models. Assuming a status-quo average R&D expenditure of 1.39% of provincial GDP, in conjunction with a provincial GDP growth rate of 1.39%, our results predict a net positive increase in facility CO_2eq. emissions. More specifically, this result means that across all 225 firms we analyzed, a R&D shock reduces emissions 184 kt to 303 kt; while a GDP-growth shock, of the same magnitude, increases CO_2eq. emissions by 806 kt to 4,034 kt. The net outcome of these two effects is an additional 622 kt to 3,930 kt of CO_2eq. emissions pollution from a subset of industrial facilities in Canada (we analyze 225 of the total 596 industrial facilities reporting to ECCC). Considering that cumulative total emissions across all of Canada was approximately 716 megatonnes of carbon dioxide equivalent (Mt CO_2eq.) in 2017, adding another ~4 Mt CO_2eq. from a subset of industrial facilities across Canada, means that in order to achieve national emissions reduction targets other sectors will have to be more aggressive with their emissions reduction actions. This is if Canada still intends to meet its Paris Agreement emissions reduction target, of 524 MtCO_2eq., by 2030 (Government of Canada, 2019b).

In line with our final objective, to explore the dynamic and spatial linkages of industrial pollution, we find evidence to suggest a firm's emissions are temporally dependent. We find a significant, positive relationship between past and present emissions levels, which suggests that facilities with higher historical pollution, are more likely to emit more pollution in the present compared to other firms, on average. This result is predicted through the work of Kolstad and

Krautkraemer (1993), who suggest pollution is likely accumulate and become more evident in the long run; and the path dependence literature which suggests that high start-up costs and positive feedback loops (economies of scale) tend towards facilities getting locked-in to a particular technological regime through time (Goodstein, 1995).

In addition to the dynamic effects of pollution, our study finds evidence to suggest that positive spatial spillovers of pollution or 'emissions-mimicking' behaviors exist between neighboring firms in close geographical proximity. In order words, we find on average, that a facility surrounded by comparatively high-polluting facilities is significantly more likely to exhibit high-polluting behaviors, and vice versa for low-polluting firms. Although we propose decomposing the mechanism of spatial spillovers of pollution is an area worthy of future research, due to our informal knowledge of Canadian regulation and land-zoning trends we hypothesize that this effect most likely occurs due to a combination of all four theories presented in the literature review (location-specific regulation, industry agglomeration, 'best practices' of pollution control passes between firms, and 'yardstick competition' between firms to gain social license). As predicted by the spatial spillovers literature, our study confirms the significance of including a spatial-lag of pollution explanatory variable in the empirical analysis of industrial firm emissions.

6.1 Policy Implications

Although we find the marginal emissions effect of technological change to be relatively small for industrial emitters, our results support the hypothesis that industrial firms are responding to incentives to implement technological advancements that lower emissions, on average. The exploration of the mechanism, through which technological change reduces industrial emissions, is not formally explored in this thesis; however, our informal knowledge of

Canadian and provincial carbon pricing regulation allows us to provide two insights that may inspire future analysis.

The first insight is that sector-competitive industrial emissions regulations (such as Alberta's 2018 Carbon Competitiveness Incentive Regulation and the Government of Canada's 2019 Output-Based Pricing System), impose two unique signals to large industrial facilities (Good, 2018). Under this competitive regulatory regime, each facility in the same sector (e.g. distilling) is ranked and assigned an 'emissions threshold' relative to its peers in the same sector. If a facility operates at a lower emissions intensity than its assigned emissions threshold, it earns 'emissions performance credits' that it can sell on the offsets market. If a facility emits more than this threshold, it has to meet it compliance obligation by either paying into a fund, buying offsets from other facilities, or by implementing emissions reduction technology to lower its compliance costs. In theory, facilities are able to anticipate increases to emissions pricing through time, and would be incentivized to implement lower emissions technologies relative to their peers in order to lower the costs of operating, as well as earn and sell credits at a price of $30/tonne (Alberta CO_2eq. price per tonne, in 2018). As this type of regulation creates two unique incentives, analyzing firms that operate within and without industrial carbon pricing regimes may be a good starting-point for understanding the mechanism through which emissions reduction technology permeates the industrial landscape. Further, since 'sector-competitive' industrial carbon pricing regimes are still in their infancy nationally, empirically exploring how different mixtures of incentives (credits vs. compliance costs) influence emissions reduction technology adoption may be a fruitful area of future research in the coming years in Canada.

The second insight into how large industrial facilities may be implementing emissions reduction technologies through time, is that provincial and national governments may be largely subsidizing the costs. Within Alberta alone there are many agencies and programs that administer emissions reduction technology funding, with the goal of: ‘reducing emissions, increasing competitiveness, lowering carbon compliance costs, and improving energy efficiency through technology and equipment upgrades’ (Government of Alberta, 2019). A handful of current programs and agencies in Alberta include: Sector-Specific Industrial Energy Efficiency (SIEE) Program; Oil Sands Innovation Fund (OSIF); Industrial Energy Efficiency funding under the Cost Containment Program (CCP); Energy Efficiency Alberta (EEA); and others. Depending on the accessibility and detail of public program expenditure data, empirically evaluating the effectiveness of emissions reductions outcomes from these funding agencies and programs may uncover interesting insights surrounding how firm’s make technological decisions that influence environmental performance.

The main policy application of our study is the result that technological advancements significantly reduce average industrial firm emissions, yet not at a rate that is not large enough to counteract the positive emissions effect associated with increased economic activity. Our analysis suggests that if the rate of technology adoption does not grow, the pollution associated with increases in economic activity will significantly dominate the emissions decreases associated with emissions reduction technology adoption. Given our estimates, it is likely that governments will have to implement more stringent measures in order to achieve the desired level of pollution for social welfare outcomes.

In conclusion, governments and environmental non-profits, seeking to address the problems of climate change and pollution, may need to devote more resources towards evaluating the effectiveness of technological change as a way to achieve desired pollution outcomes. Our analysis contributes to this ongoing conversation by providing an estimate of the industrial emissions effect associated with technological change, measured through R&D expenditures, using a spatial lag dynamic panel data model. We suggest that additional insights may be gleaned from future empirical analysis surrounding the mechanisms through which firms are incentivized to adopt emissions reduction technologies.

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