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Essays in Environmental Economics

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Abstract

This thesis presents three chapters that delve into various aspects of environmental economics and policy impacts. The first chapter investigates the influence of environmental regulations on the Canadian manufacturing sector. Over the past two decades, the sector has achieved a 40% reduction in air pollution emissions, primarily due to regulatory interventions prompting technological adjustments within the industry. The study introduces a novel model linking firm production choices to environmental regulations, distinguishing between the primary effects of environmental tax adjustments and secondary effects from technological shifts. Analysis of data from 2004 to 2021 suggests that the primary regulatory effect is responsible for 70% of the emission reduction but incurs a 35% loss in aggregate manufacturing output, whereas the secondary effect accounts for the remaining 30% reduction with a lesser impact on output.

The second chapter explores the effectiveness of cloud seeding as a hail damage mitigation strategy in Alberta, a region prone to severe hailstorms. Using a dynamic panel data model, this chapter assesses the impact of cloud seeding on radar-measured Vertically Integrated Liquid (VIL) across various storm stages, utilizing data from 187 seeded storm tracks between 2011 and 2020. The findings indicate differential impacts of seeding, with reductions in VIL in the earlier stages of storms and a slight increase in the later stages, leading to varied effectiveness. Simulation results reveal minimal cost savings from current practices, but adjusting seeding strategies could yield significant annual damage cost savings in Calgary, estimated at 23 million CAD.

The third chapter quantifies the economic implications of public disagreement on climate change in the United States, a major emitter of greenhouse gases. Despite scientific consensus on climate change, a substantial portion of the U.S. remains skeptical, creating a 'public climate change agreement gap.' This study estimates the effects of enhancing public agreement on climate change perceptions on subsequent greenhouse gas emissions and calculates the potential welfare benefits. Findings suggest that reducing the public agreement gap could lead to significant welfare improvements, potentially amounting to annual gains of up to $78 billion.

Keywords

Chapter 1: air pollution, manufacturing emissions, abatement technologies, environmental regulations, productivity, Porter's hypothesis.

Chapter 2: hailstorm damage, cloud seeding, hail suppression program, dynamic panel data model, Blundell and Bond estimator, system general method of moments (GMM), benefit-cost analysis.

Chapter 3: public perception of Climate Change, climate change, greenhouse-gas emissions (GHG), Instrumental Variable, two-stage least square (2SLS), social cost of carbon, welfare analysis, temperature anomaly.

Summary for Lay Audience

The first chapter investigates how environmental regulations have influenced the Canadian manufacturing sector's ability to clean up pollution. Over the last twenty years, this sector has reduced its air pollution emissions by 40%. This significant decrease is largely due to environmental regulations that have prompted companies to adopt new technologies, some of which even improve productivity. The study developed a model to better understand how firms' production decisions are influenced by these regulations, analyzing the data from 2004 to 2021. It was found that the direct effects of these regulations accounted for 70% of the emission reductions but also led to a 35% decrease in overall production output. Technology changes motivated by regulations accounted for the remaining 30% of emission reductions and a smaller 3% reduction in output.

The second chapter delves into the effectiveness of cloud seeding—a technique used to reduce hail damage—in Alberta, Canada. Known for its severe hailstorms, this region's weather interventions were assessed through a model analyzing data from 2011 to 2020. The findings suggest that while cloud seeding can reduce hail intensity in the earlier stages of a storm, it may actually increase intensity in the later stages. The current approach to cloud seeding was found to yield minimal cost savings in terms of damage, leading to recommendations for policy adjustments that could potentially save Calgary an estimated 23 million CAD annually in storm damage repairs.

The third chapter addresses the economic consequences of public disagreement on climate change in the United States, a major contributor to global greenhouse gas emissions. Despite a scientific consensus on the risks of climate change, a considerable portion of the U.S. population remains skeptical. This chapter quantifies the potential benefits of increasing public agreement on climate change, linking greater public consensus to lower emissions and significant potential welfare gains. It argues that closing the gap in public climate agreement could significantly enhance national welfare.

Co-Authorship Statement

I acknowledge that the third chapter of this thesis was developed from my summer paper, updated, and published (the following citation) in co-authorship with my dearest friend and colleague, Jafar El-Armali. His friendship and collaboration have been a cornerstone of this work's success.

El Armali, Jafar, and Meghdad Rahimian. ”Public climate change agreement and GHG emissions in the US.” International Review of Applied Economics (2024): 1-7.

Epigraph

”Do not seek the water, (but) get thirst, so that the water may gush forth from above and below.”

—Rumi, (13th Century)

Dedication

To my beloved parents, who, although no longer with us, have always been the beacon guiding my pursuit of knowledge. Your encouragement has been my foundation, and your memory continues to inspire every step I take.

To Dr. Gavahi, whose unwavering support and guidance helped fill the void left behind and steered me through the challenges of this journey—I am eternally grateful for your mentorship.

To Faezeh, the love of my life, who stands steadfastly by my side, your presence makes every obstacle surmountable and every moment brighter.

And to my beautiful daughters, Fatemeh and Zahra, who fill my world with joy and purpose—you are the reason I aspire to be the best version of myself, setting an example that I hope inspires you to chase your own dreams.

This thesis is not just a culmination of my academic endeavor but a testament to your profound impact on my life.

Acknowledgements

My deepest gratitude to my supervisor, Salvador Navarro, whose invaluable guidance, steadfast support, and profound mentorship have been instrumental throughout this research endeavor. My sincere thanks also go to my committee members, Ananth Ramanarayanan and Victor Aguiar, whose insightful feedback and constructive criticism have significantly enriched this study.

I am also profoundly grateful to Professor Tim Conley, who has truly supported me throughout my PhD journey. His provision of teaching opportunities, financial assistance during challenging times, and the readiness with which he provided recommendations have been invaluable to my academic and personal growth.

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Completing the second chapter would not have been possible without the great assistance of my dear friend Reza Najafi, who provided crucial radar data on hailstorms in Calgary and shared his expertise on the meteorological science of hailstorms. Additionally, I owe a debt of gratitude to Keith Porter for providing the essential procedures to map the results with hail sizes and damage savings.

Special thanks to my friend and colleague, Phuong Vu, for her invaluable feedback on the first chapter. Her insights greatly enhanced the clarity of the arguments presented.

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List of Nomenclature

$\alpha_{i,s}$	Productivity booster measure
$\bar{z}_{i,s}$	Emission intensity
β_s	Expenditure share on sector s goods
$\gamma_{R,s}$	Sector outcomes adjustment factor (OAF)
$\gamma_{Z,s}$	Sector emissions adjustment factor (EAF)
ϕ_s^*	Zero-profit productivity cut-off
$\pi_{i,s}$	Profit using technology i in sector s
ρ_s	Price mark-up (i.e., $\sigma_s/\sigma_s - 1$)
σ_s	Elasticity of substitution in sector s
$\tau_{i,s}$	Tax rate (in terms of factor unit per ton of emissions)
θ_s	Pareto distribution of sector productivity, shape parameter
φ	Productivity draw
$\varphi_{i,k}$	Productivity cut-off that a firm is indifferent between technologies i and k
$e_{i,s}$	Input emission intensity, tonnes of emissions per unit of input
f_s^e	Sunk cost of drawing productivity
$f_{i,s}$	Fixed cost of adoption of technology i

$G(.)$	Productivity cumulative distribution
$g(.)$	Productivity density distribution
i	Abatement technology indicator
L	Aggregate factor supply
$l_{i,s}$	Factor of production in sector s
M_s	Number of successful entrants in sector s
m_s	Pareto distribution of sector productivity, location parameter
M_s^e	Number of attempted entrants in sector s
$p_{i,s}$	Price of sector s
$q_{i,s}$	Quantity of products
R_s	Sector revenue
$r_{i,s}$	Revenue from sales
s	Consumer expenditure on sector
s	Sector indicator
T_s	Environmental regulation
t_s	Environmental tax
Z_s	Emission from sector s
$z_{i,s}$	Emission (in tonnes) from production

Preface

This thesis represents the fulfillment of my journey to address pressing questions related to the role of technology and information in environmental economics that have captivated my curiosity for some time. Each section embodies a unique story and reflects my motivations for pursuing these research topics.

The first essay, ”Environmental Regulations and Manufacturing Clean-up,” delves into the contentious debates between policymakers and industries regarding the potential costs of environmental regulations. This topic emerged from my desire to understand the dynamics and implications of these heated discussions, which often pit economic growth against environmental sustainability. By examining the role of air pollution control technologies in the Canadian manufacturing sector, I aim to shed light on how regulations influence both economic performance and environmental outcomes.

In the second essay, ”Measuring the Impact of Cloud Seeding on Hail Damage: A Ten-Year Dynamic Panel Data Analysis of Hailstorm Suppression Program in Alberta,” I responded to my curiosity after hearing the news about a 1.2 Billion dollar hail damage in Calgary. Knowing that the Alberta Hail Suppression Program (AHSP), initiated in 1996, has been conducting massive efforts yearly to protect Calgary from hail damage, I was curious about the reasons behind rising hail damage during the last decade. My question was whether the program, using cloud seeding technology, effectively impacts the cost reduction of hail.

The third essay, ”The Effect of Public Agreement on GHG Emissions,” addresses a broader societal issue: the public perception gap regarding scientific findings on climate change in the United States. It highlights the critical role of public opinion in shaping climate policy and its potential to drive significant reductions in GHG emissions. Despite a strong scientific consensus on climate change, public opinion in the United States remains divided, with a substantial portion of the population either doubting its existence or its potential harm. This gap in public agreement on climate change has significant implications for GHG emissions and for implementing and succeeding climate change policies.

Chapter 1

1 Environmental Regulations and Manufacturing Clean-up

The Role of Abatement Technologies in Canadian Manufacturing Clean-up

1.1 Introduction

Over the recent decades, despite increased output, there has been a significant decrease in manufacturing air pollution emissions in the US (Levinson, 2015) and Europe (Brunel, 2017). Canada's manufacturing sector also followed this trend. Figure 1.1, shows that primary air pollutants[1] released by Canadian manufacturing plants have decreased by an average of 46% between 2004 and 2021. The consistent reduction in manufacturing air pollution emissions occurred even during a period of increase in manufacturing output between 2009 and 2019.[2]

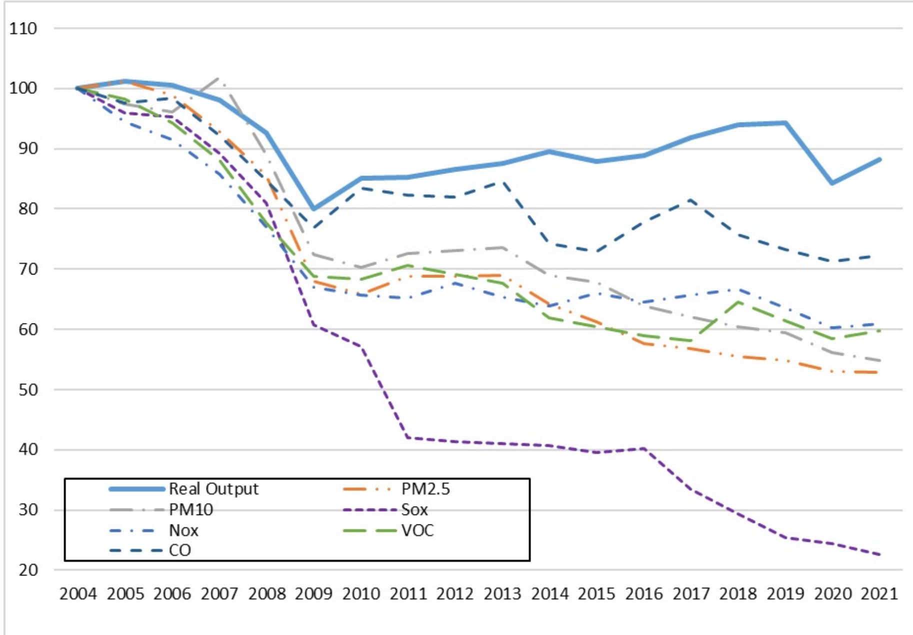
Studies indicate that the key determinant of manufacturing clean-up is reducing emission intensity (i.e., emissions per unit of output) within individual sectors, the so-called technique effect, mainly attributable to the impact of environmental regulations and the subsequent productivity and technological changes in the sector. (Levinson, 2009; Shapiro and Walker, 2018; Najjar and Cherniwchan, 2021).

Environmental regulations encourage manufacturers through combinations of technology

[1]Primary air pollutants from the manufacturing sector include a range of substances released during production that significantly impact environmental and human health. These pollutants mainly include Particulate Matter (PM), Volatile Organic Compounds (VOCs), Sulfur Oxides (SOx), Nitrogen Oxides (NOx), and Carbon Monoxide (CO).

[2]During this period, the average reduction in emissions was 46%: $PM_{2.5}$ (47.1%), PM_{10} (45.2%), SOx (77.5%), NOx (39.1%), VOC (40.2%), and CO (28.8%). Meanwhile, manufacturing output has gone through three distinct phases. Firstly, there was an initial 20% decrease from the peak 2005 to the lowest point in 2009. Secondly, there was a 15% increase and a bounce back to a second peak in 2019. Finally, there was a 10% decrease in 2020, followed by a 5% recovery in 2021.

Figure 1.1: Canada's Manufacturing Real Output and Pollution Emissions(2004=100)



Notes: The figure shows trends in the aggregate output of Canadian manufacturers versus aggregate manufacturing pollution emissions of particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen oxide (NOx), volatile organic compounds (VOCs), carbon monoxide (CO), and Sulfur oxides (SOx). The aggregate output is nominal manufacturing shipments deflated by the industry price index (Statistic Canada, tables 16-10-0047 and 18-10-0032-01). Aggregate manufacturing pollution is from the National Pollutant Release Inventory (NPRI) from 2004 to 2021.

and performance-based policies. These policies mandate the adoption of specific pollution control technologies or set targets for air quality that industries must meet.[3] These regulations drive technological changes that reduce emissions intensity and induce significant behavioral shifts in manufacturing practices, resulting in a notable reallocation of resources from pollution-intensive sectors to cleaner ones. Empirical studies have documented the impact of such regulations on manufacturing pollution reduction, as seen in the effects of Canada's air quality standards (Najjar and Cherniwchan, 2021) and the US Clean Air Act (Correia et al., 2013).

[3]Examples of such policies are Canada's emission standards for vehicles and engines (Government of Canada, 2021) and the New Source Performance Standards (NSPS) in the US Clean Air Act (US Environmental Protection Agency, 1970a). Performance-based standards, like the Canadian Ambient Air Quality Standards (CAAQS) (Government of Canada, 2012) and the National Ambient Air Quality Standards (NAAQS) in the US (US Environmental Protection Agency, 1970b), require industries to achieve specific pollutant concentration levels.

This paper studies firms' responses to environmental regulations that have led to the observed changes in manufacturing emissions and output in Canada. Specifically, I decompose the effects of these regulations into two components: the impact of changes in policy stringency with unchanged technologies (the primary effects) and the impact of regulation-induced technological changes (the secondary effects). By assuming emissions as a byproduct of production, regulations tend to mitigate pollution emissions by levying taxes on emissions or imposing penalties on polluting manufacturers to increase the marginal cost of production and decrease their output. Meanwhile, these taxes and penalties incentivize the regulated firms to invest in adopting technologies to reduce emissions efficiently, compromising less of their output. These technological shifts tend to decrease the emission intensity and, as a result, reduce emissions.

Moreover, decomposing the regulation effects into the primary and secondary effects of regulations allows for assessing whether more stringent environmental regulations can bring about technological changes that increase productivity and output in regulated industries, consistent with the strong version of Porter's hypothesis (Porter and van der Linde, 1995).[4]

I developed a quantitative model of firms' technology and pollution emission choices to comply with environmental regulations within Canada's manufacturing sector. This model is grounded in a general equilibrium framework, in which heterogeneous firms endogenously choose from a list of abatement technologies facing environmental tax. These technologies differ based on their effects on firm productivity (e.g., some can improve productivity), emissions per input unit, and adoption costs. Significantly, my model accommodates varied firm responses to uniform changes in environmental regulations. Drawing inspiration from models in the literature (Cherniwchan et al., 2017; Shapiro and Walker,

[4]The Porter's Hypothesis states that environmental regulations, if well-designed, can stimulate innovation, enhance competitiveness, and potentially improve efficiency and offset compliance costs. This opposes the conventional notion that more stringent regulations reduce the output of regulated industries. Empirical evidence for the hypothesis is mixed (Ambec et al., 2013).

2018; Najjar and Cherniwchan, 2021), my model differentiates between the primary impacts of environmental regulations on emissions and output through price mechanism and the secondary effects stemming from shifts in technologies. The model is designed for straightforward parameter estimation, analyzing various counterfactual scenarios, and assessing Porter's hypothesis.

I achieve a few objectives by combining this model with data from Canadian manufacturers. First, I seek to quantify the overall regulatory burden of intersecting environmental policies [5] over time. I then decompose the implied stringency of regulations to the primary influences of evolving tax rates and the secondary influences of technological transitions within sectors. An increase in the tax rate raises the marginal cost of regulated firms, thereby increasing the overall sector sales price. This change in relative sector prices leads to the reallocation of output shares across sectors, referred to as the primary effect of regulations. The magnitude of changes in the sector sales price and output share is also contingent upon the technology choices of the regulated firms facing higher environmental taxes. Access to cleaner and more productive abatement technologies at relatively low costs can temper the significant price and output swings and reduce pollution emissions cost-effectively, referred to as the secondary effect of regulations.

My findings indicate that since the 2012 updates to major air pollution regulations[6], the average implied tax rate for regulated industries has increased by a factor of 1.6. This change has also altered the pattern of regulation effects on emission reductions. Recent studies (Holladay and LaPlue III, 2021 and Najjar and Cherniwchan, 2021) highlight the dominant effect of technologies in manufacturing clean-up. In contrast, my findings emphasize that the primary effect of regulation drives reductions in key air pollutants, accounting for at least two-thirds of the reductions. The remainder stems from regulation-induced techno-

[5] I refer the reader to Environment and Canada [2024] for the list and details of these regulations

[6] In 2012, the Canadian Council of Ministers of the Environment (CCME), excluding Quebec, decided to adopt the new Air Quality Management System (AQMS). This system includes updated ambient air quality standards, integral to its framework (Canadian Council of Ministers of the Environment, 2024).

logical shifts within these sectors.

Over the last decade, the increasing role of the primary effect of regulations in emission reductions suggests that further tightening may lead to significant output losses. Although I found minimal support for Porter's hypothesis in certain regulated sectors, this study highlights the limited capacity for technological adaptation within regulated sectors. Manufacturers cannot rely on affordable solutions to reduce emissions without largely compromising their output.

This paper contributes to the literature in three ways. First, I distinguish between the primary and secondary effects of the overall regulatory burdens that manufacturing firms encounter due to local and national air pollution regulations. I assume that available abatement technologies are not homogeneously continuous. I contest the conventional belief that implementing abatement technology inevitably reduces regulated firms' efficiency. In practice, some technologies are cleaner and improve productivity. Naturally, the trade-off is that these superior features often come with a higher adoption cost [7]. This assumption allows for varied responses from different firms to environmental regulations. Regulated firms may not necessarily decrease their output to comply with regulations. The model suggests that some highly productive firms may be able to increase their output by adopting cleaner and more efficient technologies.

Second, the model can determine the additional impact of regulations on sector-level variables that arise solely due to technological shifts brought about by regulation changes. It summarizes these effects into two sufficient statistics. The sector's outcome adjustment factor (OAF) indicates the additional impact of regulatory-induced technological changes on the sector's minimum productivity required to engage in market competition. It tends to increase entry cost and average sector productivity, reducing sector sales price and increasing sector output. The other key factor is the sector's emissions adjustment factor

[7] I refer the reader to Appendix A to see a few examples of different types of abatement technologies.

(EAF), which represents the regulatory-induced technological changes that tend to reduce aggregate pollution emissions.

When firms have access to cost-effective, cleaner, and more productive technological alternatives, they can adapt to stricter regulations, reducing their emissions without significantly increasing their prices and compromising their output. This situation manifests itself in a larger OAF and smaller EAF. By comparing these factors, I identify sectors that have had to undergo significant output and resource reallocation to achieve equivalent emissions reductions. This provides insights into the technological composition of different sectors and has important policy implications.

Lastly, this methodology adds to the flexibility and tractability of the current theoretical models. My model incorporates discrete and heterogeneous technologies and a technology selection mechanism in a tractable way. It explains the hierarchical order of technologies, which depends on their adoption costs and productivity-enhancing capacities. This hierarchy emerges directly from firms' profit maximization. Firms strategically eliminate strictly dominated technologies; thus, profit maximization filters out suboptimal technologies.

As a result, when faced with environmental taxation, firms respond heterogeneously. Firms at the lower end of the productivity spectrum may exit the market. In contrast, those with higher productivity might select costlier abatement solutions that offer cleaner production with only a marginal dip in efficiency. Yet, the highest-productivity firms can adopt technologies that increase productivity and ensure clean production.

Consequently, the model allows for a diverse range of production functions within a sector, including decreasing, constant, and increasing returns to scale. Moreover, it emphasizes the role of fixed costs in determining firms' technology choices and profit-maximizing decisions.

The paper is structured as follows: Section 2 decomposes Canadian manufacturing emissions. Section 3 describes the model, while Section 4 explains firms' technology selection procedure under regulation and provides a model solution. Section 5 provides an overview of the data, and Section 6 outlines the estimation procedure. Section 7 analyzes counterfactual scenarios and results. Finally, Section 8 concludes.

1.2 Decomposition of Manufacturing Emissions

This section discusses the statistical decomposition of Canadian manufacturing emissions between 2004 and 2021. I use an analytical approach in Levinson [2015] to determine the effects of changes in manufacturing output, sectors' output shares, and sectors' emission intensities on the overall trends of manufacturing emissions.[8]

In equation 1.1, the total manufacturing emissions in a given year (Z_t) is the aggregate of emissions from individual sectors. Tones of emissions from each sector in year t, (z_{st}), is determined by the sector's output value (q_{st}) and its emission intensity ($\bar{z}_{st}$). Sectors' output can be expressed as a fraction (θ_{st}) of the manufacturing output (Q_t).

$$Z_t = \sum_s z_{st} = \sum_s q_{st}\bar{z}_{st} = Q_t \sum_s \theta_{st}\bar{z}_{st} \tag{1.1}$$

The decomposition method examines the counterfactual trends in the aggregate emissions from their initial state at the base year (Z_t/Z_0).

Figure 1.2 illustrates observed and counterfactual trends in manufacturing emissions.[9] The figure's topmost solid line (blue) shows counterfactual manufacturing emissions assuming a variable manufacturing output but fixed sector output shares and emission intensities at 2004 values. The gap between this line and the horizontal benchmark (set at 100) quantifies

[8]When referring to "sectors," I mean the manufacturing industries classified under the 4-digit North American Industry Classification System (NAICS) codes from 3111 to 3399. When referring to manufacturing, I mean the industries classified under the 2-digit NAICS code from 31 to 33.

[9]The statistical methods used to decompose these trends are detailed in Appendix B.

the effect of manufacturing output fluctuations on manufacturing emissions, known as the *scale effect*.

The intermediate dashed line (red) presents a scenario where manufacturing output and sector output shares vary while sector emission intensities are unchanged from their 2004 levels. The disparity between this line and the uppermost line quantifies the impact of shifting output shares across sectors on manufacturing emissions, known as the *composition effect*.

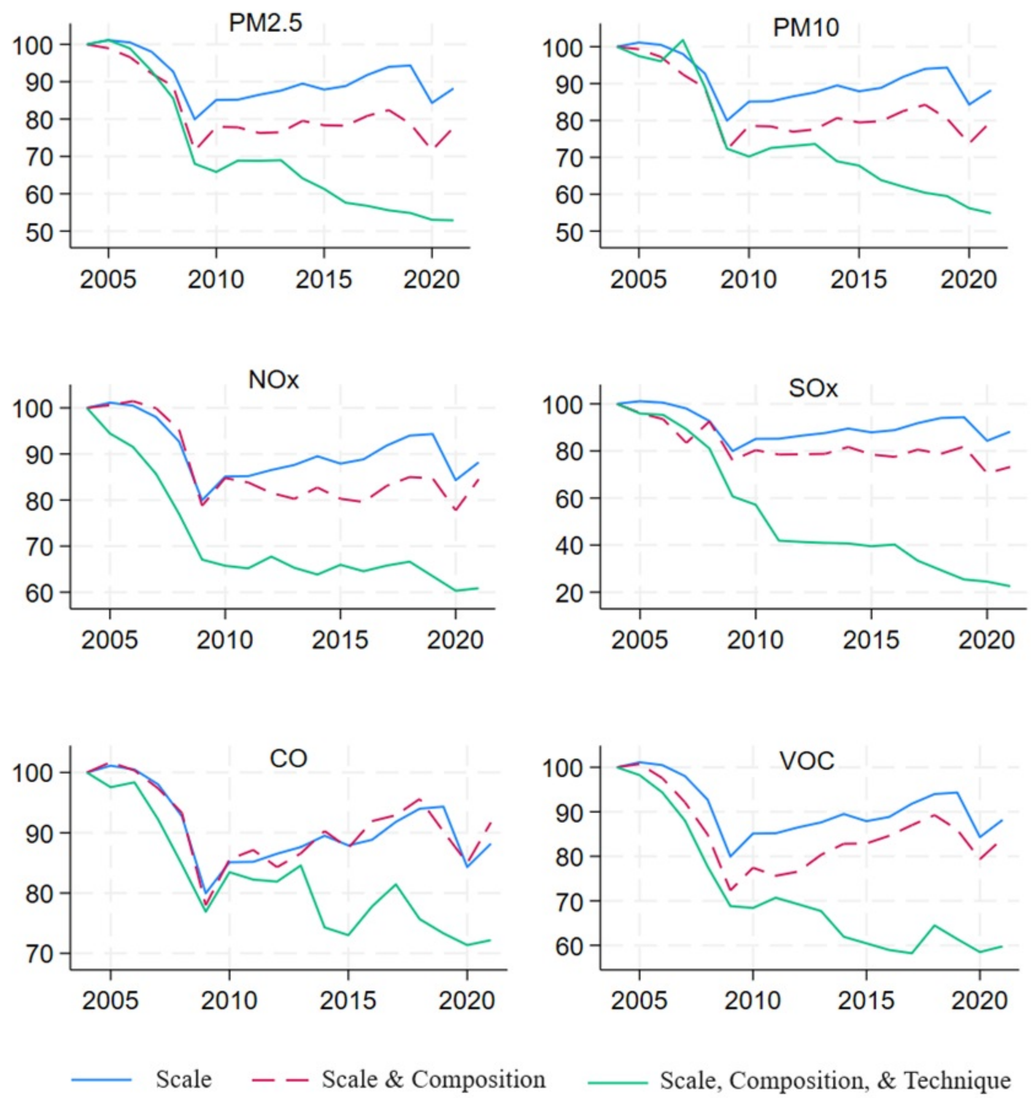
The figure's lowest solid line (green) shows the actual manufacturing emission trends, including variable manufacturing output, sector output shares, and sector emission intensities. The difference between this line and the middle dashed line quantifies the effect of changes in sector emission intensities, known as the *technique effect*.

Table 1.1: The average shares of scale, composition, and technique effects in air-pollutant emissions reduction between 2004-2021

	$PM_{2.5}$	PM_{10}	SOx	NOx	VOC	CO
Total Emissions Reduction (%) from 2004 to 2009 (Period of declining output)	32.0	27.6	39.3	32.9	31.2	23.1
Scale effect (%)	38.9	-5.8	13.9	16.0	8.0	16.5
Composition effect (%)	61.3	-18.2	83.6	-4.5	36.4	-0.1
Technique effect (%)	-0.1	124.1	2.5	88.5	55.6	83.5
Total Emissions Reduction (%) from 2010 to 2021 (Period of rising output)	15.1	17.5	38.1	6.2	9.0	4.7
Scale effect (%)	30.4	34.6	18.7	32.2	31.9	54.3
Composition effect (%)	27.2	27.2	16.0	17.8	18.4	-1.9
Technique effect (%)	42.4	38.2	65.3	50.0	49.6	47.6

Table 1.1 shows the average shares of scale, composition, and technique effect for the periods of reducing and increasing manufacturing output. There were differences in the nature of emissions reduction between these two periods. The average scale effect was more pro-

Figure 1.2: Canadian Manufacturing Emission Decomposition 2004 - 2021 (2004=100)



Notes: This figure displays observed and counterfactual emission trends derived from the statistical decomposition. The uppermost solid (blue) line shows how manufacturing emissions would look with only scale effects, excluding composition and technique effects. The dashed line (red) showcases how would manufacturing emissions look without the technique effect. The bottom solid (green) line shows the observed emission trends in the presence of scale, composition, and technique effects. Data source: The manufacturing and sector outputs are nominal shipments deflated by the industry price index from Statistic Canada, tables 16-10-0047 and 18-10-0032-01. Manufacturing emissions are from the National Pollutant Release Inventory (NPRI) from 2004 to 2021.

nounced in the second period (14.6% compared to 33%), while the average composition effect was larger in the first period (26.4% compared to 17.5%). Finally, the average technique effect was the dominant factor for emissions reduction in both periods (49% and 59%).

The breakdown of manufacturing emissions presented in Figure 1.2 indicates that from 2004 to 2021, and particularly after 2009, neither the scale nor the composition effect was the main driver of emissions trends. Instead, the Technique effect was primarily responsible for the observed emission shifts.[10]

It should be emphasized that while the statistical decomposition of manufacturing emissions may provide valuable insights into the sources of changes in emissions, it does not offer a comprehensive understanding of the specific behaviors of consumers and firms or the market mechanisms that drive these trends.[11]

Our goal is mainly to understand the role of environmental regulations and the corresponding firms' responses to comply with regulations by changing their price, output, or production processes in deriving the observed scale, composition, and technique effects. Therefore, it is important to supplement statistical decomposition with a theoretical framework to gain a more nuanced and comprehensive understanding of the complex drivers of emissions changes in the manufacturing sector.

1.3 Model

This paper presents a Melitz-based (Melitz, 2003) general equilibrium model incorporating firm-level responses to environmental policies, including the decision-making process for

[10]The results align with the results of studies conducted by Levinson [2009, 2015] and Shapiro and Walker [2018] on US manufacturing emissions.

[11]Empirical studies attempted to gain a deeper understanding of how manufacturing emissions can be reduced by decomposing the technique effect. For instance, Holladay and LaPlue III [2021] used data on plant-level output and emissions to break down the technique effect into three categories: reallocation, selection, and process effects. The reallocation effect looks at how shifts in the output share of products within a sector can affect sector emission intensity. The selection effect examines the impact of firms entering or exiting the market on sector emission intensity. Finally, the process effect considers the remaining part of the technique effect that can be attributed to firms changing their production processes, affecting the sector emission intensity.

various available abatement technologies[12] The model represents the simplified yet representative characteristics of pollution-generating sectors.

The model's framework considers various firm responses, such as endogenous entry and exit, production output, and technologies for reducing pollution. The model also considers differences in productivity levels among firms, which affects their choice of abatement technologies. This results in varying emissions and output levels within and across sectors.[13]

I analyze a closed economy with a representative consumer with one productive factor supplied inelastically. The following three subsections outline the model's assumptions, describe the data used in the analysis, and detail the approach for estimating parameters and counterfactual analysis.

1.3.1 Preferences

The representative consumer has the following utility function:

$$U = \prod_s \left(\left[\int_{\omega \in \Omega_s} q_s(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\beta_s} \tag{1.2}$$

Equation (1.2) describes CES[14] utility across product varieties within a sector and Cobb-Douglas preferences across sectors. The representative agent maximizes utility by allocating expenditures across varieties of goods ω from the Ω_s of goods produced by sector s. The

[12] Melitz-based model has been widely used in similar literature, including the model estimated in Shapiro and Walker [2018] and the theoretical framework in Najjar and Cherniwchan [2021], from which this paper draws significant inspiration.

[13] I exclude the effect of changes in terms of trade from the model since studies find a small contribution to the role of trade-induced changes on manufacturing clean-up. For example, Levinson [2009] finds that changes in industrial composition induced by trade have little effect on U.S. manufacturing clean-up. Also, Shapiro and Walker [2018] find that compared to the contribution of other factors, such as productivity growth, environmental regulations, and changes in the share of consumers' expenditure on manufacturing goods, changes in trade have a negligible effect on manufacturing clean-up.

[14] The CES utility implies a decreasing marginal utility of a variety and increasing utility in the total measure of varieties (Shapiro and Walker, 2018). This utility function provides a convenient aggregate description of production across sectors.

parameter β_s denotes the share of expenditure dedicated to sector s, where $\sum_s \beta_s = 1$. The variable $q_s(\omega)$ is the quantity of variety ω goods in sector s. The sector-specific parameter $\sigma_s > 1$ is the elasticity of substitution across varieties.[15]

1.3.2 Abatement Technologies

Each sector has a range of abatement technologies, $i_s = 0, 1, 2, ..., K_s$. This range includes the option of non-abatement or continued operation under business-as-usual technology, termed as $i_s = 0$, and numerous technologies available in the sector.

The defining attributes of abatement technologies are threefold. The first determinant is the *input emission intensity* metric, $e_{i,s}$, representing the quantity of pollution discharged per unit of the factor of production. Compared to business-as-usual technology, alternative technologies are less polluting, with fewer emissions produced during manufacturing. This is represented by $e_{0,s} \geq e_{i,s}$, where $i_s = 0, 1, 2, ..., K_s$.

The second determinant is the *productivity booster* metric $\alpha_{i,s}$. The impact of an abatement technology on productivity is gauged through this metric. Business-as-usual technology is demonstrated by $\alpha_{0,s} = 1$. However, adopting an alternative technology could either augment or decrease productivity. State-of-the-art technologies are those abatement measures that amplify a firm's productivity, as depicted by $\alpha_{i,s} > 1$. Conversely, second-tier technologies represent abatement alternatives that curtail a firm's productivity, as illustrated by $\alpha_{i,s} < 1$.

Lastly, the third determinant is the *fixed cost of adoption* $f_{i,s}$, indicating that minimizing pollution emissions and improving productivity comes at a cost, denoted by $f_{0,s} \leq f_{i,s}$,. The

[15]Consumers may experience disutility caused by the total amount of pollution generated in the economy. Studies in behavioral economics suggest that consumers tend to underestimate or ignore emissions levels while making consumption decisions. For instance, a study by Attari et al. [2010] demonstrated that individuals tend to underestimate energy consumption and savings across various appliances, indicating that they may not make optimal decisions for minimizing energy use.

assumptions for these defining factors are summarized in Table 1.2.[16]

Table 1.2: Factors that define abatement technologies $i_s = 0, 1, 2, ..., K_s$

Factors	Assumptions
Input emission intensity	$e_{0,s} \geq e_{i,s}$
Productivity booster	$\alpha_{0,s} = 1$, $\alpha_{i,s} > 0$
Fixed cost of adopting	$f_{0,s} \leq f_{i,s}$,

It is reasonable to assume that the fixed cost of adopting any abatement technology, denoted by $f_{i,s}$, is positively correlated with the productivity-to-input emission intensity ratio, represented by $\alpha_{i,s}/e_{i,s}$. This assumption is intuitive as it suggests that adopting abatement technologies that are both cleaner and more productive is more expensive.

$$f_{i,s} = f(\alpha_{i,s}/e_{i,s}) \tag{1.3}$$

In order to prioritize the abatement technology set, I rank the technologies based on their fixed cost of adoption ($f_{i,s}$) from the cheapest to the most expensive, with business-as-usual technology being ranked as 0 and the most expensive technology being ranked as K_s.[17]

1.3.3 Heterogeneous Firms

Entrepreneurs sink f_s^e to draw productivity φ from a productivity distribution. I assume that the productivity distribution is Pareto with cumulative distribution function as follows:

$$G_s(\varphi) = 1 - \left(\frac{m_s}{\varphi}\right)^{\theta_s} \tag{1.4}$$

[16]These types of abatement technologies exist in real life. Appendix A includes several abatement technology examples from various manufacturing sectors.)

[17]Equation (1.3) will assist in explaining a stylized fact that firms with higher productivity have lower emission intensity, which we will discuss in the next section.

where the scale (location) parameter m_s describes the sector's productivity and the shape parameter θ_s describes the dispersion of productivity draws within a sector s.[18]

After observing the productivity draw, entrepreneurs engage in monopolistic competition[19] under an environmental regulatory regime. Conditional on choosing to operate, they choose prices p, abatement technology i from the set of available technologies to maximize profits given by:

$$\Pi_{i,s}(\varphi) = \pi_{i,s}(\varphi) - wf_s^e$$
$$\pi_{i,s}(\varphi) = p_{i,s}(\varphi)q_{i,s}(\varphi) - w\ell_{i,s}(\varphi) - w\ell_{i,s}^{\tau}(\varphi) - wf_{i,s} \tag{1.5}$$

where w is the economy-wide factor price. The profit function $\pi_{i,s}(\varphi)$ has several terms. A firm with a productivity φ [20] sells to the consumer at the price of $p_{i,s}(\varphi)$. It hires $\ell_{i,s}(\varphi)$ units of productive factor (labor)[21] to produce the following quantity:

$$q_{i,s}(\varphi) = \alpha_{i,s}\varphi l_{i,s}(\varphi) \tag{1.6}$$

and receive revenue $p_{i,s}(\varphi)q_{i,s}(\varphi)$. Equation (1.6) implies that a firm's output depends on the productive input, $\varphi\ell_{i,s}(\varphi)$, and the productivity booster measure of abatement technology, $\alpha_{i,s}$.[22]

The production cost in equation (1.5) includes the cost of production labor, $w\ell_{i,s}(\varphi)$, the fixed cost of adopting abatement technology, $wf_{i,s}$, and the cost of regulation, $w\ell_{i,s}^{\tau}(\varphi)$,

[18] Axtell [2001] suggests that firm productivity follows a Pareto distribution.

[19] I assume that the market structure is monopolistic competition. By accounting for fixed entry costs and sector-specific mark-ups, this assumption allows firm entry and exit and reallocation of production factors and output across firms.

[20] φ also symbolizes a firm's capital level. This perspective assumes that firms with greater capital enjoy enhanced productivity, resulting in higher output and revenue.

[21] $\ell_{i,s}(\varphi)$ can also be conceptualized as a composite of immediately adjustable factors of production, including energy, raw material, and labor, with capital input endogenously prescribed through the productivity draw.

[22] The convention is to assume that $\alpha_{i,s}$ is less than one. In other words, abatement activities decrease firms' productivity. However, in this paper, $\alpha_{i,s}$ may be greater or less than one, depending on the characteristics of the available abatement technologies.

further discussed in the next section.

1.3.4 Environmental Regulation, Regulation Cost, and Emissions

Under a technology-based regulatory framework, firms that upgrade and adopt abatement technologies other than business-as-usual are exempted from the pollution tax. I can express the cost of regulation as an added cost per unit of production labor

$$w\ell^{\tau}_{i,s}(\varphi) = w\tau_{i,s}e_{i,s}\ell_{i,s}(\varphi) \tag{1.7}$$

where $\tau_{i,s}$ is what a firm pays per tonne of pollution emitted, $z_{i,s}(\varphi) = e_{i,s}\ell_{i,s}(\varphi)$, in terms of labor units.[23] As a result, the total production cost can be written as follows:

$$c_{i,s}(\varphi) = wt_{i,s}\ell_{i,s} + wf_{i,s} \tag{1.8}$$

where for simplicity, I let $t_{i,s} = 1 + \tau_{i,s}e_{i,s}$ denoting the sector regulation burden. Thus, the regulation burden on a firm utilizing business-as-usual is $t_{0,s} \geq 1$, and on a firm utilizing any other abatement is $t_{i,s} = 0$. Note that each sector's regulatory burden is unique, underscoring the sector-specific nature of regulation. To illustrate this, assume that the pollution tax, τ, is uniform across all sectors. In this scenario, the regulatory burden, t, increases with the sectors' input emission intensity under business-as-usual technology. Consequently, dirtier sectors bear a larger regulatory burden.

Emissions can also be considered as a by-product of production and are an increasing function of output given by

$$z_{i,s}(\varphi) = \bar{z}_{i,s}(\varphi)q_{i,s}(\varphi), \tag{1.9}$$

where $\bar{z}_{i,s}(\varphi)$ is emission intensity measured by the tonnes of emissions per unit of output. Emission intensity depends on the productivity of the firm and the choice of abatement tech-

[23] Here, I used the definition of input emission intensity or emissions per unit input, $e_{i,s} = z_{i,s}(\varphi)/\ell_{i,s}$.

nology. Using equation (1.9) and the definition of input emission intensity, $e_{i,s} = z_{i,s}(\varphi)/\ell_{i,s}$, emission intensity is given by

$$\bar{z}_{i,s}(\varphi) = \frac{e_{i,s}}{\alpha_{i,s}\varphi} \tag{1.10}$$

Finally, it is presumed that the revenue generated from these pollution taxes is ultimately expended on rent-seeking activities.[24]

1.3.5 Competitive Equilibrium

The competitive equilibrium is defined by allocations for consumers $\{q(\omega)\}_{\forall\omega\in\Omega_s,\forall s}$, allocations for firms $\{i, p_s\}_{\forall s}$, such that given the factor price w, entry fixed cost $\{f_s^e\}_{\forall s}$, environmental policy $\{\tau_s\}_{\forall s}$, and characteristics of abatement technologies $\{e_{i,s}, \alpha_{i,s}, f_{i,s}\}_{i=0}^{K_s} \forall s$: (i) Consumers maximize their utility, (ii). Firms maximize their profits, and (iii) the factor market clears:

$$L = L^e + L^f + L^p + L^\tau, \tag{1.11}$$

where the factor supply L is allocated to four uses: paying the fixed cost of drawing productivity L^e; pollution abatement L^f; engaging in production L^p; and paying pollution taxes L^τ.

1.4 Sector Technological Composition and Technology Selection Under Environmental Regulation

One of the model's unique characteristics is that it structures the technological composition of the sector in a way that only requires two sufficient statistics to measure the overall impact of technological changes on the sector's emissions and output. These statistics can

[24]In this model, I deliberately sidestep the complexities of investment frictions, obstructions in the labor market, and progressions in research and development that potentially yield more efficient abatement technologies to concentrate on answering the overarching query: How do the properties of prevailing abatement technologies facilitate manufacturing clean-up?

summarize the effects of abatement technologies without measuring every single characteristic of the technologies.[25] To understand this better, it is essential to know how firms select technologies in this model. For that, I provide theoretical and graphical illustrations[26] presented in propositions 1 to 4 (See Appendix D for the mathematical proofs of the propositions.)

1.4.1 The Process of Sequentially Eliminating Strictly Dominated Technologies

Propositions 1 to 3 explain a procedure of eliminating strictly dominated technologies. Through propositions 1 to 3, I show that firms select only a handful of potentially numerous abatement technologies in the sector, and these technologies can be organized sequentially according to their required fixed cost of adoption and productivity booster measure. In proposition 3, I show that firms with higher productivity choose more efficient and cleaner abatement technologies facing environmental tax. Finally, in proposition 4, I conclude that the pollution intensity of firms is decreasing in productivity.

I mathematically represent a firm's profit function in sector s in equation (1.5).

$$\pi_{i,s}(\varphi) = B_s \left(\frac{\alpha_{i,s}}{t_{i,s}}\right)^{\sigma_s - 1} \varphi^{\sigma_s - 1} - w f_{i,s} \tag{1.12}$$

where $B_s = \frac{A_s}{\sigma_s}\left(\frac{1}{w\rho_s}\right)^{\sigma_s - 1}$ is a sector-specific multiplier, and i is the optimal abatement technology that maximizes the firm's profit (See the derivation details in Appendix C). $t_{i,s} = 1$ if the firm chooses any abatement technology from the list.

[25]The model looks like it has much freedom regarding firms' technology selection. It does not limit the number of available technologies in the sector. Thus, virtually the number of technology-related parameters, including productivity booster, input emission intensity measures, and fixed cost of adoption, can be massive. Also, looking at the engineering documents of all available abatement technologies in manufacturing sectors is not feasible. Even if I could do that, the engineering documents do not explain how the technology affects firms' productivity or the monetary cost of adopting it.

[26]In their theoretical framework, Najjar and Cherniwchan [2021] use similar graphical illustrations to analyze the effects of technologies on sector profit and revenue.

The profit function is linear in productivity. Thus, I can draw profit, π_s, versus productivity, φ^{σ_s-1}, a line that the slope can change by the technology's ratio of productivity booster measure over tax $\alpha_{i,s}/t_{i,s}$. The intercept of that line is $-wf_{i,s}$.

For simplicity, I drop all s subscriptions from the notations in the propositions. Also, with the loss of generality, I assume $w = 1$.

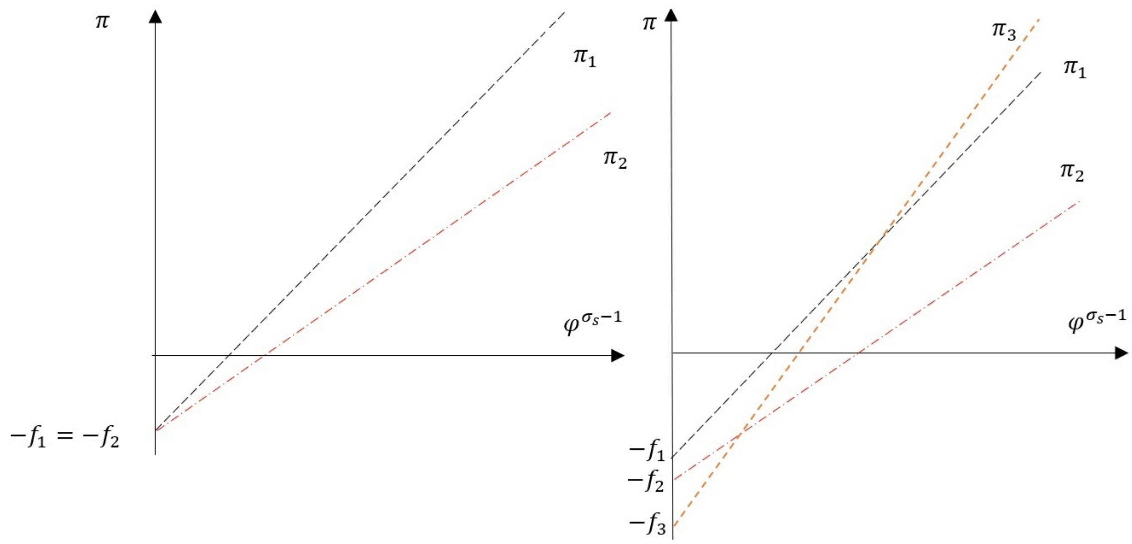
Proposition 1: Adoption costs of abatement technologies are unique. Consider a set of abatement technologies denoted by $\{i\}_0^K$ for a given sector s, where each technology i is associated with a fixed adoption cost f_i and a productivity booster measure α_i. This set can be refined into a subset $\{j\}_0^k$ by excluding technologies strictly dominated by other technologies. Each technology possesses a unique fixed cost of adoption in this refined subset, ensuring that for any two distinct technologies m and n in the subset, the corresponding fixed costs are distinct, i.e., $f_m \neq f_n$.

The left panel in Figure 1.3 represents a graphical illustration of this proposition. Suppose two abatement technologies, 1 and 2, in a sector (I dropped the s subscription for simplicity). The fixed cost of adoption is the same for both, but the productivity booster measure of 1 is greater than 2: $\alpha_1 > \alpha_2$. As a result, the profit of any firm using technology 1 is greater than its profit when it uses technology 2. Thus, technology 2 is strictly dominated by technology 1 and is eliminated from the list.

Proposition 2: Larger adoption cost of an abatement technology is associated with higher productivity booster measure, α. Consider the sequence of abatement technologies $\{i\}_1^K$ in a given sector s, each associated with a fixed cost of adoption f_i and a productivity booster measure α_i. This set can be refined into a subset $\{j\}_1^k$ by excluding technologies strictly dominated by other technologies. In this refined subset, the technologies are ordered such that for any two distinct technologies other than business-as-usual, $m \neq 0$ and $n \neq 0$, if $f_m < f_n$, then it necessarily follows that $\alpha_m < \alpha_n$.

The right panel in Figure 1.3 represents a graphical illustration of this proposition. Suppose

Figure 1.3: Elimination of Strictly Dominated Technologies - Proposition 1 and 2



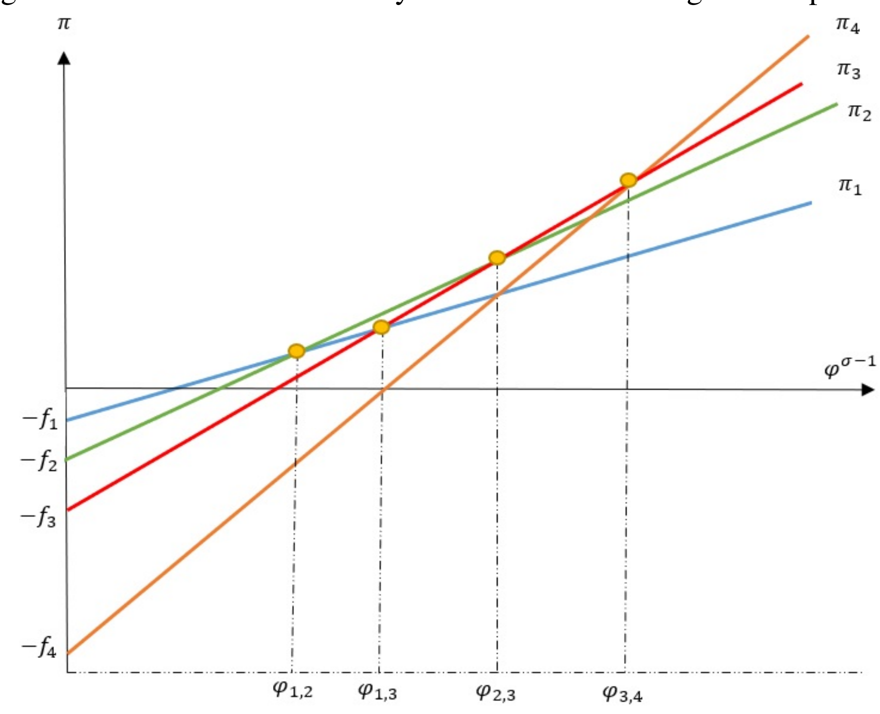
there are three abatement technologies: 1, 2, and 3 in a sector (I dropped the s subscription for simplicity). The fixed costs of adoption are ordered as $f_1 < f_2 < f_3$, but the productivity booster measures are ordered differently: $\alpha_2 < \alpha_1 < \alpha_3$. As observed, technology 2 is strictly dominated by technology 1; hence, it is eliminated from the list. The remaining technologies satisfy the condition provided by proposition 2: $f_2 < f_3 \implies \alpha_2 < \alpha_3$.

Proposition 3: Larger adoption cost is associated with higher productivity cut-off. Consider the sequence of abatement technologies $\{i\}_1^K$ within sector s, each characterized by a fixed adoption cost f_i, and a productivity booster measure α_i. Suppose that $\varphi_{m,n}$ is the productivity level in which a firm is indifferent between choosing technologies m and n from $\{i\}_1^K$. This set can be condensed into a subset $\{j\}_1^k$ by excluding strictly dominated technologies, where, for any three consecutive and distinct technologies $k \neq 0$, $k+1$, and $k+2$ where $f_k < f_{k+1} < f_{k+2}$, the productivity thresholds must satisfy $\varphi_{k,k+1} \leq \varphi_{k,k+2} \leq \varphi_{k+1,k+2}$, and the following condition must hold.

$$\frac{f_{k+1} - f_k}{\alpha_{k+1}^{\sigma-1} - \alpha_k^{\sigma-1}} \leq \frac{f_{k+2} - f_k}{\alpha_{k+2}^{\sigma-1} - \alpha_k^{\sigma-1}} \leq \frac{f_{k+2} - f_{k+1}}{\alpha_{k+2}^{\sigma-1} - \alpha_{k+1}^{\sigma-1}}. \tag{1.13}$$

Figure 1.4 represents a graphical illustration of this proposition. In this example, a sector has four technologies ordered by the fixed cost of abatement and productivity booster measure, such that $f_1 < f_2 < f_3 < f_4$ and $\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$. They meet the requirements of Propositions 1 and 2. However, firms will not opt for technology 2 because other technologies offer higher profit gains at any productivity level φ. That is, from $\varphi = 0$ to $\varphi = \varphi_{1,3}$, firms prefer adopting $i = 1$, from $\varphi = \varphi_{1,3}$ to $\varphi = \varphi_{3,4}$, firms prefer adopting $i = 3$, and firms with $\varphi > \varphi_{3,4}$ prefer $i = 4$. Thus, technology 2 is eliminated from the list. Proposition 3 filters out these kinds of technologies. In this instance, the order of productivity cut-offs violates the requirements of Proposition 4, which prescribes that $\varphi_{1,2} < \varphi_{1,3} < \varphi_{2,3} < \varphi_{3,4}$.

Figure 1.4: Elimination of Strictly Dominated Technologies - Proposition 3



Note that the validity of Propositions 1 to 3 is established independently of any specific functional form for the fixed cost of adoption. The functional form introduced in equation (1.3) is only used in the proof of Proposition 4.

Proposition 4: The higher the firm's productivity, the lower its emission intensity.

The emission intensity of firms in sector s, denoted by $\bar{z}_i(\varphi) = e_i/\alpha_i\varphi$, is decreasing in productivity, φ.

1.4.2 Sector Technological Composition

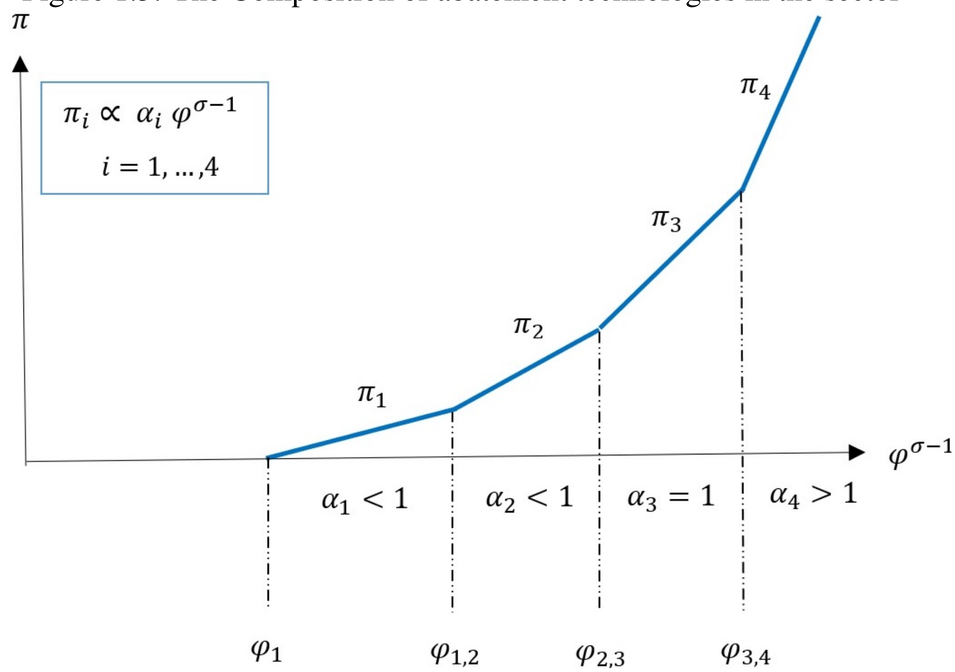
Propositions 1 to 3 provide an algorithm to compile the list of all available abatement technologies in the sector. After the process of elimination, the remaining abatement technologies construct a profit envelope that I call the sector's *technological composition*. It consists of an ordered sublist of abatement technologies and corresponding productivity cut-offs. Figure 1.5 illustrates a hypothetical composition of a sector's abatement technologies. It shows the prevailing abatement technology for the range of productivity. The sector's abatement technologies include four technologies, 1 to 4, and their respective productivity cut-offs. These technologies include two alternatives, $\alpha_1 < 1$ and $\alpha_2 < 1$, a retrofit $\alpha_3 = 1$, and a state-of-the-art technologies with $\alpha_4 > 1$. Firms with higher productivity have access to cleaner and more efficient technologies, which are more costly.

1.4.3 Technology Selection Under an Environmental Regulation

Proposition 5 defines how firms choose between technologies facing environmental tax given the composition of the sector's abatement technologies (the mathematical proof is detailed in Appendix B.)

Proposition 5. Consider the ordered set of technologies $\{i\}_0^K$ within sector s that survived from excluding strictly dominated technologies mentioned in proposition 3. Each technology is characterized by a fixed adoption cost f_i, and a productivity booster measure α_i, with $i = 0$ representing the business-as-usual technology (i.e., $\alpha_0 = 1$ and $f_0 < f_i \forall i = 1, ..., K$). Suppose that sector s is subjected to an environmental tax, t, which only applies to the firms utilizing the business-as-usual. Depending on the tax rate, if exists, there is a unique abatement technology $i^* \in \{i\}_1^K$ and productivity cut-off φ_{0,i^*} that firms with $\varphi \leq \varphi_{0,i^*}$ choose

Figure 1.5: The Composition of abatement technologies in the sector



Notes: In this figure, a hypothetical sector has four surviving abatement technologies, eliminating strictly dominant technologies. The abatement technologies can be ordered by their fixed adoption costs and productivity booster measures. As a result, the sector has a sequence of ordered productivity cut-offs, $\varphi_1 < \varphi_{1,2} < \varphi_{2,3} < \varphi_{3,4}$, indicating how firms would decide to use an abatement technology based on their productivity φ.

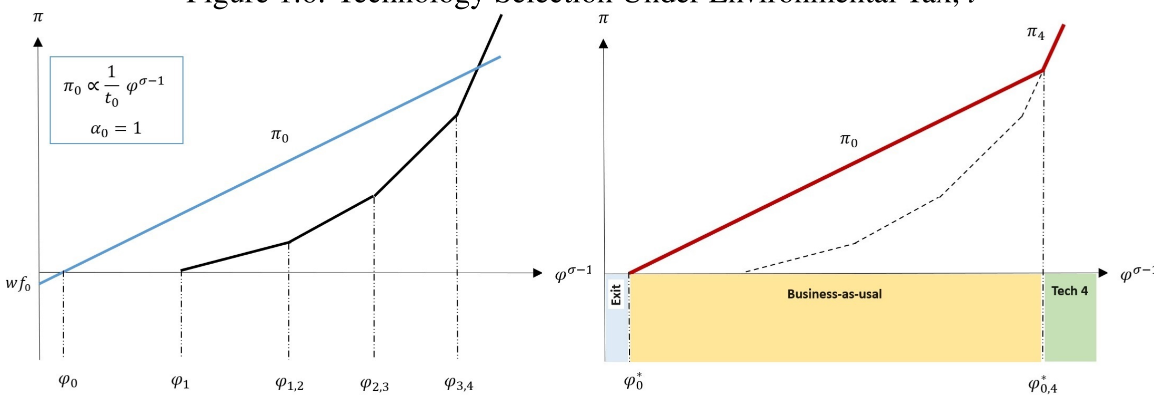
using business-as-usual, and firms with $\varphi \geq \varphi_{0,i^*}$ choose technologies other than business-as-usual. In this case, for technologies $i^* - 1$, i^*, and $i^* + 1$, the productivity thresholds must satisfy $\varphi_{i^*-1,i^*} \leq \varphi_{0,i^*} \leq \varphi_{i^*,i^*+1}$, and the tax rate falls in the following range:

$$\frac{f_{i^*+1} - f_{i^*}}{f_{i^*} - f_0} . \frac{1}{\alpha_{i^*+1}^{\sigma-1} - \alpha_{i^*}^{\sigma-1}} \leq t_0^{\sigma-1} \leq \frac{f_{i^*} - f_{i^*-1}}{f_{i^*-1} - f_0} . \frac{1}{\alpha_{i^*}^{\sigma-1} - \alpha_{i^*-1}^{\sigma-1}} . \tag{1.14}$$

The position of technology in a sector depends on its technological composition and the magnitude of the environmental tax. As environmental regulations become stricter, more firms are likely to adopt abatement technologies to comply with regulations.

Figure 1.6 represents a hypothetical regulated sector. In the left panel, the solid line, pi_0, represents the profit related to business-as-usual technology under environmental tax, t. In the right panel, entrepreneurs with productivity measures less than φ_0^* decide not to enter the market. Firms with $\varphi_0^* < \varphi < \varphi_{0,4}^*$ decide to pay wf_0 and operate under business-as-usual. A small group of high-productivity firms, $\varphi > \varphi_{0,4}^*$ decides to pay wf_4 and operate under technology 4.

Figure 1.6: Technology Selection Under Environmental Tax, t



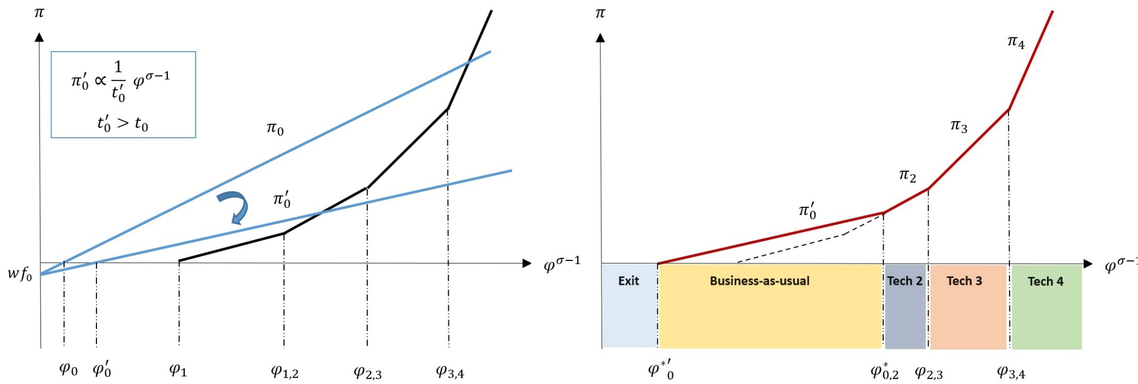
Notes: In this figure, a hypothetical sector has a composition of four surviving abatement technologies. The profit line related to business-as-usual, π_0, under environmental tax, t, is shown in the left panel. In the right panel, firms either exit or select a technology that maximizes their profit. The solid red line shows the profit envelope.

Suppose a new tax, $t' > t$, increases the marginal cost of business-as-usual; thus, as it is illustrated in the left panel of figure 1.7, the profit line π_0 rotates downward to π_0'. As a result, in the right panel, some firms that previously chose business-as-usual decide to exit the market; some keep on using business-as-usual, and some switch to technologies 2, 3, and 4. The solid red line shows the final profit envelope in the sector.

In this example, the change in the sector's total factor productivity (TFP) and output under higher regulation is ambiguous. Under the higher environmental tax, some firms selected technology 2, which is less efficient but cleaner. Some chose business-as-usual and retrofit (technology 3) that does not change their productivity. A group of high-productivity firms could afford technology 4, which is cleaner and boosts their productivity. The overall effect on TFP depends on the weighted summation of firms' productivity.

This model allows increases in the sector's TFP and output under higher environmental taxes. I combine the model with the Canadian manufacturing pollution and production

Figure 1.7: Technology Selection Under Environmental Tax, $t' > t$



Notes: This figure shows as the tax rate increases, $t' > t$, firms previously chose business-as-usual decide either to exit the market, keep on using business-as-usual, or choose abatement technologies based on their productivity. The solid red line shows the final profit envelope in the sector.

data to estimate parameters and check if there is evidence that TFP and output growth have occurred for any regulated manufacturing sector, confirming a strong version of Porter's hypothesis.

1.5 Model Implications

A few fundamental equilibrium conditions that detail firms' behavior under environmental regulations can briefly capture the model's logic. For a competitive equilibrium, these conditions should hold at any given time. In the next section, I use these equations to recover the historical sector productivity, environmental regulation, and technological shocks to the Canadian manufacturing sector (See derivations in Appendix C.)

1.5.1 Market Clearing Condition

The Market clearing condition says that aggregate demand and supply for factors must equate, as shown in equation (1.11). I combine this with the implication of the free entry condition and the assumption of an inelastic labor supply. Thus, the aggregate input cost must match the aggregate manufacturing revenue at any point in time:

$$wL_0 = R \tag{1.15}$$

1.5.2 Free Entry Condition

The equilibrium state is achieved when the cost of drawing productivity equals the expected profit from participating in market competition.

$$wM_s^e f_s^e = M_s \bar{\pi}_s \tag{1.16}$$

The left-hand side describes the total cost of entrepreneurs drawing productivity, and the right-hand side is the total profit gains of those participating in the market. $\bar{\pi}_s$ is the average profit of operating firms in the sector, which follows the below expression.

$$\bar{\pi}_s = \frac{\sigma_s - 1}{\theta_s - \sigma_s + 1} w f_{0,s} \gamma_{R,s} \tag{1.17}$$

where $\gamma_{R,s}$ is the Sector's Outcome Adjustment Factor (OAF) in the following equation:

$$\gamma_{R,s} = 1 + \left(t_{0,s}^{\sigma_s-1} \alpha_{i^*,s}^{\sigma_s-1} - 1\right)^{\frac{\theta_s}{\sigma_s-1}} \left(\frac{f_{0,s}}{f_{i^*,s} - f_{0,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1} \tag{1.18}$$

$$+t_{0,s}^{\theta_s} \left(\alpha_{i^*+1,s}^{\sigma_s-1} - \alpha_{i^*,s}^{\sigma_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}} \left(\frac{f_{0,s}}{f_{i^*+1,s} - f_{i^*,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1} + \cdots$$

$$+t_{0,s}^{\theta_s} \left(\alpha_{K,s}^{\sigma_s-1} - \alpha_{K-1,s}^{\sigma_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}} \left(\frac{f_{0,s}}{f_{K,s} - f_{K-1,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}$$

(See derivations in Appendix C.) OAF is a sufficient statistic that is always greater than or equal to one ($\gamma_{R,s} \geq 1$) and summarizes the impact of technological changes induced by environmental taxation on the sector's average profit. This metric is important as it measures the impact of regulations on sector outcomes without necessarily measuring all characteristics of the underlying abatement technologies.

It is worth noting that there is an increasing relationship between the environmental tax $t_{0,s}$ and $\gamma_{R,s}$ since $t_{0,s}$ is positively included in the equation. However, $t_{0,s}$ also has another effect on $\gamma_{R,s}$. As the tax rate increases, the number of abatement technologies that firms use in the sector also increases. A few high-productivity firms use the most expensive abatement technologies when the tax rate is low. As a result, only some of the expensive abatement technologies (e.g., K_s) may appear on the right-hand side of the equation (1.18).

In contrast, less expensive abatement technologies are used by less productive firms when the tax rate rises. Therefore, the cut-off technology i^* in equation (1.18) depends on the tax rate. Since all these added segments are positive, $\gamma_{R,s}$ increases as the tax rate increases. Furthermore, a larger difference between the productivity-enhancing measures of consecutive technologies or a lower difference between their abatement fixed costs is generally associated with a higher $\gamma_{R,s}$. The precise degree of this increase is contingent upon the composition of abatement technologies employed within the sector.

OAF enables us to compare a sector's profitability with a counterfactual scenario where only business-as-usual technology is available. In this counterfactual scenario, OAF is equivalent to one and remains unchanged over time.

The free entry condition further implies that the total profit in the sector after accounting for the cost of drawing productivity is zero, $\Pi_{i,s}(\varphi) = 0$; hence, sector revenue must match the total input cost (including the cost of drawing productivity), $wL_s = R_s$.

1.5.3 The Zero-Profit Productivity Cut-off

To derive the unique equilibrium zero-profit cut-off for the model, I have combined equations (1.16) to (1.20). This equilibrium cut-off represents a productivity level at which entrepreneurs are indifferent between participating in the market or staying aside. This cut-off is sufficient to explain all other equilibrium productivity cut-offs in which firms switch to more efficient and cleaner technologies.

$$\varphi_s^* = m_s \gamma_{R,s}^{\frac{1}{\theta_s}} \left(\frac{f_{0,s}}{f_s^e} \frac{\sigma_s - 1}{\theta_s - \sigma_s + 1} \right)^{\frac{1}{\theta_s}} . \tag{1.19}$$

(See derivations in Appendix C.) Equation (1.19) explains the role of sector productivity, m_s, and OAF, $\gamma_{R,s}$, in determining the equilibrium zero-profit productivity cut-off.

In the model, the sector productivity m_s is the scale factor of the Pareto distribution of productivity, as shown in equation (1.4). It represents the minimum level of productivity that can be drawn in the sector. A positive sector productivity shock raises this bar, which results in fewer entrepreneurs willing to draw productivity and participate in the market.

Similarly, increased OAF, caused by increased tax rates, raises the minimum productivity requirement for market participation. This, in turn, increases the zero-profit productivity threshold, leading some of the least productive firms in the market to opt out of the competition.

As we have seen in the previous sections, the zero-productivity cut-off is important. All other productivity cut-offs, where firms are indifferent between keeping their current technology or switching to a new one, are proportional to the zero-productivity cut-off. If there is any shock to the zero-productivity cut-off, all other cut-offs will shift proportionally while maintaining the same order.

I will use the equation (1.19) to relate the number of surviving firms in the market to the zero-productivity cut-off and, hence, to the sector's OAF.

1.5.4 Successful Entry

I determine the probability of successful entry using the cumulative Pareto productivity distribution. This probability must match the proportion of the entire pool of entrepreneurs that draw productivity.

$$\frac{M_s}{M_s^e} = \left(\frac{m_s}{\varphi_s^*}\right)^{\theta_s} \tag{1.20}$$

Equation (1.20) shows the relationship between the ratio of entrants to entrepreneurs and the ratio of sector productivity to zero-profit cut-off. Successful entry occurs when the probability of productivity draws is greater than the zero-profit productivity cut-off. If the zero productivity cut-off increases, such as through the imposition of higher environmental tax rates, the likelihood of successful entry decreases.

In this context, the number of firms that survive is proportional to the inverse zero-profit productivity cut-off, $M_s \propto 1/\varphi_s^{*\theta_s}$. Thus, according to equation (1.20), the number of entrepreneurs drawing productivity measure is proportional to the inverse of $m_s^{\theta_s}$ that is $M_s^e \propto 1/m_s^{\theta_s}$.

I will use these assumptions to equate proportional changes in M_s^e and M_s with the inverse of proportional changes in $m_s^{\theta_s}$ and $\varphi_s^{*\theta_s}$. This is the main assumption used to differentiate between the effects of environmental regulations with and without abatement technologies.

1.5.5 Sector Revenue, Price, and Output

I aggregated firms' revenue and combined it with free entry condition to achieve the following expression for sector revenue:

$$R_s = \frac{\theta_s \sigma_s}{\sigma_s - 1} w M_s^e f_s^e \tag{1.21}$$

(See Appendix C for derivation) The sector revenue is unaffected by changes in environmental tax. That is, competing with other sectors, firms within a sector collectively decide to maintain the sector revenue and revenue share in the market. They do this by reallocating factors and changing output and price within the sector.

That being said, it does not mean that the sector output share remains intact by changes in environmental regulations. For that, I analyze sector price. The equilibrium sector (sales) price can be calculated using the following expression:

$$P_s = \left(\frac{\theta_s - \sigma_s + 1}{\theta_s}\right)^{\frac{1}{\sigma_s - 1}} w\rho\left(\frac{t_s}{\varphi_s^*}\right)\left(\frac{1}{M_s^e}\right)^{\frac{1}{\sigma_s - 1}} \tag{1.22}$$

(See Appendix C for derivation) Equation (1.22) is crucial for understanding how environmental taxes affect sector outcomes through the price mechanism, P_s. An increase in environmental tax rates has two effects on the sector price. Firstly, it increases the price directly via $t_{0,s}$ since higher taxes increase the costs incurred by the sector. Secondly, higher tax rates will also increase $\gamma_{R,s}$ and the zero-productivity cut-off, φ_s^*, which eliminates the lowest-productivity firms in the market and tends to reduce the sector price. The extent to which the zero-productivity cut-off increases depends on the technology composition in the sector. More accurately, the tax effect on sector price depends on the ratio: $t_s/\gamma_{R,s}^{1/\theta_s}$, and it can go in either direction.

Another crucial factor affecting a sector's price is the sector productivity, m_s, which is embodied both in φ_s^* and M_s^e. When the sector productivity increases, the zero-profit productivity cut-off increases, and the number of entrepreneurs decreases. The overall effect on the sector price is proportional to $m_s^{(\theta_s - \sigma_s + 1)/(\sigma_s - 1)}$.

I also analyze the effect of regulations on sector output, $Q_s = R_s/P_s$. Since the environmental tax does not affect sector revenue, if the sector price increases in tax, sector output declines, and if the sector price decreases in tax, sector output increases. The latter would be evidence for a strong Porter's Hypothesis. I will check for the evidence in this paper. Sector output is expressed mathematically as follows:

$$Q_s = \theta_s\left(\frac{\theta_s}{\theta_s - \sigma_s + 1}\right)^{\frac{1}{\sigma_s - 1}} f_s^e\left(\frac{\varphi_s^*}{t_{0,s}}\right)(M_s^e)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{1.23}$$

(See Appendix C for derivation.)

1.5.6 Sector Emissions and Emission Intensity

I aggregate firms' pollution emissions within a sector to find the equilibrium sector emissions as follows:

$$Z_s = \frac{\theta_s e_{0,s}}{T_s} M_s^e f_s^e \tag{1.24}$$

where T_s is the overall regulatory burden on the sector as follows

$$T_s = t_{0,s} \frac{\gamma_{R,s}}{\gamma_{Z,s}} \tag{1.25}$$

and $\gamma_{Z,s}$ is the Sector's Emissions Adjustment Factor (EAF) expressed in the following equation:

$$\begin{aligned}\gamma_{Z,s} = 1 &+ \left(\frac{e_{i^*,s} t_{0,s}^{\sigma_s}}{e_{0,s}} - 1\right)\left(\frac{t_{0,s}^{\sigma_s-1} - 1}{\frac{f_{i^*,s}-f_{0,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1} \\ &+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{i^*+1,s}\alpha_{i^*+1,s}^{\sigma_s-1} - e_{i^*,s}\alpha_{i^*,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{i^*+1,s}^{\sigma_s-1} - \alpha_{i^*,s}^{\sigma_s-1}}{\frac{f_{i^*+1,s}-f_{i^*,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1} \\ &+ \ldots \\ &+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{K,s}\alpha_{K,s}^{\sigma_s-1} - e_{K-1,s}\alpha_{K-1,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{K,s}^{\sigma_s-1} - \alpha_{K-1,s}^{\sigma_s-1}}{\frac{f_{K,s}-f_{K-1,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\end{aligned} \tag{1.26}$$

EAF is a sufficient statistic that summarizes the effect of environmental tax and technological composition on sector average pollution emissions Z_s/M_s. This metric is important because, along with OAF, it allows us to measure the collective impact of taxation and inherent technologies on sector pollution, bypassing the need to detail every characteristic of the underlying abatement technologies.

Notably, $\gamma_{Z,s} \leq 1$ and tends to decrease in environmental tax $t_{0,s}$. The precise degree of this decrease is contingent upon the composition of abatement technologies employed within the sector. In the subsequent sections, I introduce a methodology to quantify the variations in $\gamma_{Z,s}$.

The equation (1.25) demonstrates the various components of the environmental regulation burden. Firstly, the environmental tax calculates the proportional change in sector emissions, assuming no abatement technologies exist. Secondly, the effect of abatement technologies can be broken down into two parts: $\gamma_{Z,s}$ measures the effect of abatement technology on the sector's average emissions, while $\gamma_{R,s}$ shows the effect of abatement technologies on the sector's emissions via changes in output.

Suppose two sectors are facing a similar environmental tax change. In that case, the emission reduction from firms reacting to the regulation shock by choosing different abatement technologies is reflected in sectors' $\gamma_{Z,s}/\gamma_{R,s}$. In the sector where cheaper, cleaner, and more productive abatement technologies are available, there is a larger increase in $\gamma_{R,s}$ and a larger decrease in $\gamma_{Z,s}$, leading to more emission reduction and less output loss. In other words, the same tax rate transforms into a different overall regulatory burden on sectors depending on their technological composition.

The emission intensity of a sector, represented by $Z_s P_s / Rs$, is influenced by environmental taxes that impact both sector emissions and prices. The overall effect is proportional to the ratio of $\gamma_{Z,s}/\gamma_{R,s}^{1+1/\theta_s}$. This indicates that environmental tax changes only affect the emission intensity of a sector through the introduction of abatement technologies. Specifically, a sector with cheaper, cleaner, and more productive abatement technologies will experience a greater increase in $\gamma_{R,s}$ and a larger decrease in $\gamma_{Z,s}$, leading to a greater reduction in emission intensity.

1.6 Data

I combine the model with Canada's Annual Survey of Manufacturers (ASM) and National Pollutants Reporting Inventory (NPRI) to estimate the parameters and analyze the counterfactual scenarios. Data that are collected in the ASM include firms' principal industrial statistics (e.g., shipments, employment, salaries and wages, cost of materials and supplied used, cost of energy and water utility, inventories, goods purchased for resales, etc.), and commodity data (e.g., shipments or consumption of particular products). The NPRI is Canada's plant-level public inventory of pollutants releases, disposals, and transfers. The NPRI was established in 1993, and it currently collects information on more than 320 substances from over 7,000 facilities, including industrial sectors, businesses, institutions, treatment plants, and other facilities across Canada.

I used the plant-level linked dataset, NPRI-ASM, provided by the Canadian Research Data Center Network (CRDCN), which covers comprehensive manufacturers data from 2004 to 2012. I chose 2004 as the base year because of the following reasons. There have been several changes in how the ASM survey gathered data, and 2004 is the one with the largest change occurring. Moreover, 2004 was the first year that all regulated facilities provided their complete pollutant emissions data to the NPRI. There is consistent panel data for most existing pollutants from 2004 onward.

I use the NPRI-ASM dataset to estimate the Pareto distribution's shape parameter and the substitution elasticity across firms' products within a sector. Estimating the elasticity of substitution requires input costs and the total sales value for each sector. Estimating the Pareto distribution shape factor requires firm-level sales value.

The NPRI-ASM linked dataset was discontinued in 2012. I used STATCAN's tables separately for each sector from 2013-2021. Details of the tables and corresponding variables of interest are described in Table 1.3.

Table 1.3: Statistics Canada Tables

StatCan Tables	Table description	Variable(s) of interest	Frequencies
14-10-0064-01	Employee wages by industry annual	Average hourly wage rate of labor	Annually
16-10-0048-01	Manufacturing sales by industry and province, monthly	Sector revenue	Monthly
16-10-0117-01	Principal statistics for manufacturing industries, by NAICS	Price	Monthly
18-10-0267-01	Industrial product price index, by industry, monthly	Monthly price index	Monthly
18-10-0268-01	Raw materials price index, monthly	Raw materials price index	Monthly
33-10-0164-01	Business Dynamics measures by industry	Number of operational firms in the sector	Annually

These datasets use the North American Industrial Classification Standard (NAICS) codes to classify different types of manufacturing industries. The manufacturing sector's definition in this paper is based on 4-digit NAICS codes starting with 31, 32, and 33. There are 89 4-digit manufacturing industries, but as per the CRDCN vetting requirements, I merged some of the 4-digit sectors together to ensure that the requirements were met, ending up with 78 industries.[27] In Table 1.4, I list the top 3 industries that are the most polluted for each pollutant.

Table 1.4: Sectors with the largest pollution emission share for each pollutant

Pollutant	**Top 3 industries with the largest share**	**Pollutant Shares**	**Pollutant Intensity (tonnes per million dollars)**
PM25	Pulp, paper and paperboard mills	0.34	0.59
	Non-ferrous metal (except aluminum) production and processing	0.10	0.33
	Veneer, plywood and engineered wood product manufacturing	0.08	0.37
SOx	Non-ferrous metal (except aluminum) production and processing	0.62	52.38
	Petroleum and coal product manufacturing	0.10	2.37
	Pulp, paper and paperboard mills	0.07	2.88
NOx	Cement and concrete product manufacturing	0.23	7.07
	Pulp, paper and paperboard mills	0.22	1.87
	Petroleum and coal product manufacturing	0.18	0.79
VOC	Pulp, paper and paperboard mills	0.12	0.85
	Sawmills and wood preservation	0.10	0.98
	Petroleum and coal product manufacturing	0.10	0.36
CO	Alumina and aluminum production and processing	0.42	33.36
	Sawmills and wood preservation	0.23	9.98
	Pulp, paper and paperboard mills	0.11	3.53

[27] In particular, I merge sector 3121 with sector 3122; sector 3131 with sector 3132; sector 3161 with sector 3162; sector 3274 with sector 3279; sector 3211 with sector 3312; sector 3342 with sector 3343; sector 3361 with sector 3362; and sector 3364 with sector 3365.

1.7 Estimation

1.7.1 Estimating the Pareto Distribution Shape Factor θ and Elasticity of Substitution σ

Using the methodology introduced by Shapiro and Walker [2018], as referenced in Table 2, I have separately estimated the elasticity of substitution and the shape parameter of the Pareto distribution for each sector. Specifically, I determined σ_s by analyzing the relationship between the value of shipments and production costs. I derived the Pareto shape parameter θ_s by regressing the logarithm of a firm's sales rank against the logarithm of its sales, drawing data from the 2004 Canada's Annual Survey of Manufacturers. The outcomes affirm my assumption that $\theta_s - \sigma_s + 1 > 0$.[28]

I adopted the proportional change technique from Shapiro and Walker [2018], initially used by Dekle et al. [2008]. This approach's advantage is its ability to sidestep certain hard-to-measure parameters when examining variable changes.

To deploy this, any variable x in my model becomes $\hat{x}$, with the proportional change given by $\hat{x} = \frac{x'}{x_0}$. Accordingly, the equations (1.21) to (1.15) transform into the following equations.

1.7.2 Proportional Changes in Wages

From the market clearing condition equation (1.15), I find the following:

$$\hat{w} = \hat{R} \tag{1.27}$$

[28] See the methodology details in Appendix E

Equation (1.27) describes the equilibrium factor price changes and equates that to changes in aggregate manufacturing revenue alterations.

1.7.3 Proportional Changes in Zero-profit Productivity Cut-off

Using equation (1.19), I write the following expression for counterfactual proportional changes in zero-profit productivity cut-off.

$$\hat{\varphi}_s^* = \hat{m}_s \hat{\gamma}_{R,s}^{\frac{1}{\theta_s}} \tag{1.28}$$

Equation (1.28) relates changes in zero-profit cut-off to sector productivity and changes in OAF. The underlying assumption is other variables and parameters, namely $f_{0,s}$, f_s^e, σ_s, and θ_s are not changing over time.

1.7.4 Proportional Changes in Entrants

Changes in zero-profit cut-off (1.28) govern the successful entries competing in the market. The lower the minimum productivity required to enter the market, the higher the number of entrants. Adding the fact that $\hat{M}_s/\hat{M}_s^e = 1/\hat{\gamma}_{R,s}$ from equation (1.20), I write the following statement:

$$\hat{M}_s = (1/\hat{\varphi}_s^*)^{\theta_s} \Rightarrow \hat{M}_s^e = 1/\hat{m}_s^{\theta_s} \tag{1.29}$$

Positive shifts in sector productivity mean that the minimum required productivity increases; thus, the number of entrepreneurs attempting to enter the market decreases.

1.7.5 Proportional Changes in Sector Revenue, Price, and Output

From equation (1.21), the proportional change in sector revenue is as follows:

$$\hat{R}_s = \hat{w}\hat{M}_s\hat{\gamma}_{R,s}. \tag{1.30}$$

Equation (1.30) relates changes in OAF to changes in sector average revenue adjusted by factor price, $\hat{R}_s/\hat{w}\hat{M}_s$.

From (1.22), the proportional change in sector price is as follows

$$\frac{\hat{P}_s}{\hat{w}} = \left(\frac{1}{\hat{M}_s^e}\right)^{\frac{1}{\sigma_s - 1}} \left(\frac{\hat{t}_s}{\hat{\varphi}^*}\right). \tag{1.31}$$

Equation (1.31) connects changes in sector price to environmental tax and productivity shocks. I used this equation to calculate the historical values of changes in environmental tax.

1.7.6 Proportional Changes in Pollution Emissions

For changes in sector pollution emissions, I use equation (1.24) to write the following expression:

$$\hat{Z}_s = \frac{\hat{M}_s^e}{\hat{T}_s} \tag{1.32}$$

Equation (1.32) illustrates changes in sector emissions. Proportional changes in sector pollution are related to firm entry and environmental regulation, $\hat{T}_s = \hat{t}_s \frac{\hat{\gamma}_{R,s}}{\hat{\gamma}_{Z,s}}$.

Environmental regulation $\hat{T}_s$ includes the environmental tax, $\hat{t}_s$, and the technology instrument, $\frac{\hat{\gamma}_{R,s}}{\hat{\gamma}_{Z,s}}$. If the environmental tax remains unchanged, the technology instrument remains constant, equating to 1.

1.7.7 Proportional Changes in Manufacturing Emissions:

I aggregated emissions across all firms to evaluate changes in manufacturing emissions. The aggregate changes in manufacturing emissions from the reference year are as follows:

$$\hat{Z} = \frac{\sum_s \frac{\hat{M}_s^e}{\hat{T}_s} Z_{0s}}{\sum_s Z_{0s}} \tag{1.33}$$

where Z_{0s} is the emission of sector s at the base year.

1.7.8 Proportional Changes in Manufacturing Output:

Similarly, by aggregating output across all firms and sectors, I can evaluate changes in manufacturing output:

$$\hat{Q} = \sum_{s} (\hat{M}_s^e)^{\frac{\sigma_s}{\sigma_s - 1}} \hat{\varphi}_s^* / \hat{t}_{0,s} \left(\frac{Q_{s0}}{Q_0} \right) \tag{1.34}$$

I will use equations (1.33) and (1.34) to examine the counterfactual aggregate emissions and output scenarios.

1.7.9 Recovering Historical Values of Shocks

To comprehend how the characteristics of pollution abatement technologies, intertwined with environmental policies, shaped Canada's manufacturing pollution trajectory, I must explore counterfactual scenarios. Specific shocks mirror their factual occurrences in these scenarios, while others don't. Here, my objective is to quantify the historical values of each shock, namely sector productivity, environmental tax, and technological shocks between 2004 and 2021. I have achieved this by utilizing model implementation and sector aggregate data to separate primary shocks: productivity, environmental regulations, environmental tax, and technology shifts.

Sector Productivity Shocks

Sector productivity shocks illustrate the variations in productivity within sectors, denoted by $\hat{m}_s$. These variations are essentially shocks to the scale parameter of the sector Pareto distribution of productivity. I combine equations (1.29) and (1.27) to derive the historical values of sector productivity shocks:

$$\hat{m}_s^* = \left(\frac{\hat{R}}{\hat{R}_s} \right)^{\frac{1}{\theta_s}} \tag{1.35}$$

Proportional changes in sector productivity shocks are measured by the proportional variations of the inverse of the sector's revenue share scaled to the power of the inverse sector's shape factor in the productivity distribution.

Environmental Regulation Shocks

I combine equations (1.32), and (1.27) to derive the historical values of environmental regulation shocks:

$$\hat{T}_s^* = \frac{\hat{R}_s}{\hat{Z}_s \hat{R}} \tag{1.36}$$

Historical values of environmental tax shocks primarily stem from the proportional changes in sector price.

$$\hat{t}_s^* = \frac{\hat{P}_s \hat{R}_s^{\frac{1}{\sigma_s - 1}}}{\hat{M}_s^{\frac{1}{\theta_s}} \hat{R}^{\frac{\sigma_s}{\sigma_s - 1}}} \tag{1.37}$$

Figure 1.8 shows the average proportional changes of implied environmental tax within highly regulated manufacturing sectors from 2004 to 2021. It shows that since 2012, when the new sets of major air-pollutant regulation updates came into effect, the implied tax has continuously increased by 1.6 times.

Historical Shocks to the OAF are measured using the equation (1.30)

$$\hat{\gamma}_{R,s}^* = \frac{\hat{R}_s}{\hat{M}_s \hat{R}} \tag{1.38}$$

Similarly, the historical shocks to the EAF are measured using equation (1.32) and replacing the variables from the above three equations.

$$\hat{\gamma}_{Z,s}^* = \frac{1}{\hat{M}_s^{\frac{1}{\theta_s}}} \left(\frac{\hat{R}_s}{\hat{R}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \frac{\hat{Z}_s}{\hat{M}_s} \frac{\hat{P}_s}{\hat{R}_s} \tag{1.39}$$

where $\hat{Z}_s \hat{P}_s / \hat{M}_s \hat{R}_s$ is the proportional changes in the sector average emission intensity.

To this end, I have presented a methodology for recovering the historical shock values.

Figure 1.8: Average proportional changes of Implied Environmental Tax within Highly Regulated Sectors (3211, 3221, 3273, 3311, 3335, and 3336) (2004=1)

Notes: The implied environmental tax has continuously increased by 1.6 times from 2012 to 2021.

My model's distinctiveness lies in its ability to differentiate between the impact of environmental regulation on emission reductions in the scenario where abatement technologies are available and the counterfactual scenario in which the only available technology is business as usual.

1.8 Counterfactual Analysis

1.8.1 Methodology

In this paper I decompose the manufacturing emissions and output into the effect of underlying sector productivity, environmental regulation, and regulation-induced technological shocks, and compare the scope of effects of each shock on emissions and output.

The counterfactual scenarios are characterized by selecting values for the shocks to sector productivity, environmental tax, and technology for each year between 2004 and 2021, denoted as $\{\hat{m}_s, \hat{t}_s, \hat{\gamma}_{R,s}/\hat{\gamma}_{Z,s}\}$. These values can either be hypothetical or represent the actual historical values of these shocks. Finally, equation (1.33) and (1.34) allow us to compute and compare Canada's manufacturing pollution emissions and output under each counterfactual scenario.

The historical shock values for each year and sector, $\{\hat{m}^*_s, \hat{t}^*_s, \hat{\gamma}^*_{R,s}/\hat{\gamma}^*_{Z,s}\}$, are determined using equations (1.37) to (1.39). To decompose the emission and output changes based on distinct shocks, I examine specific counterfactual scenarios as shown below:

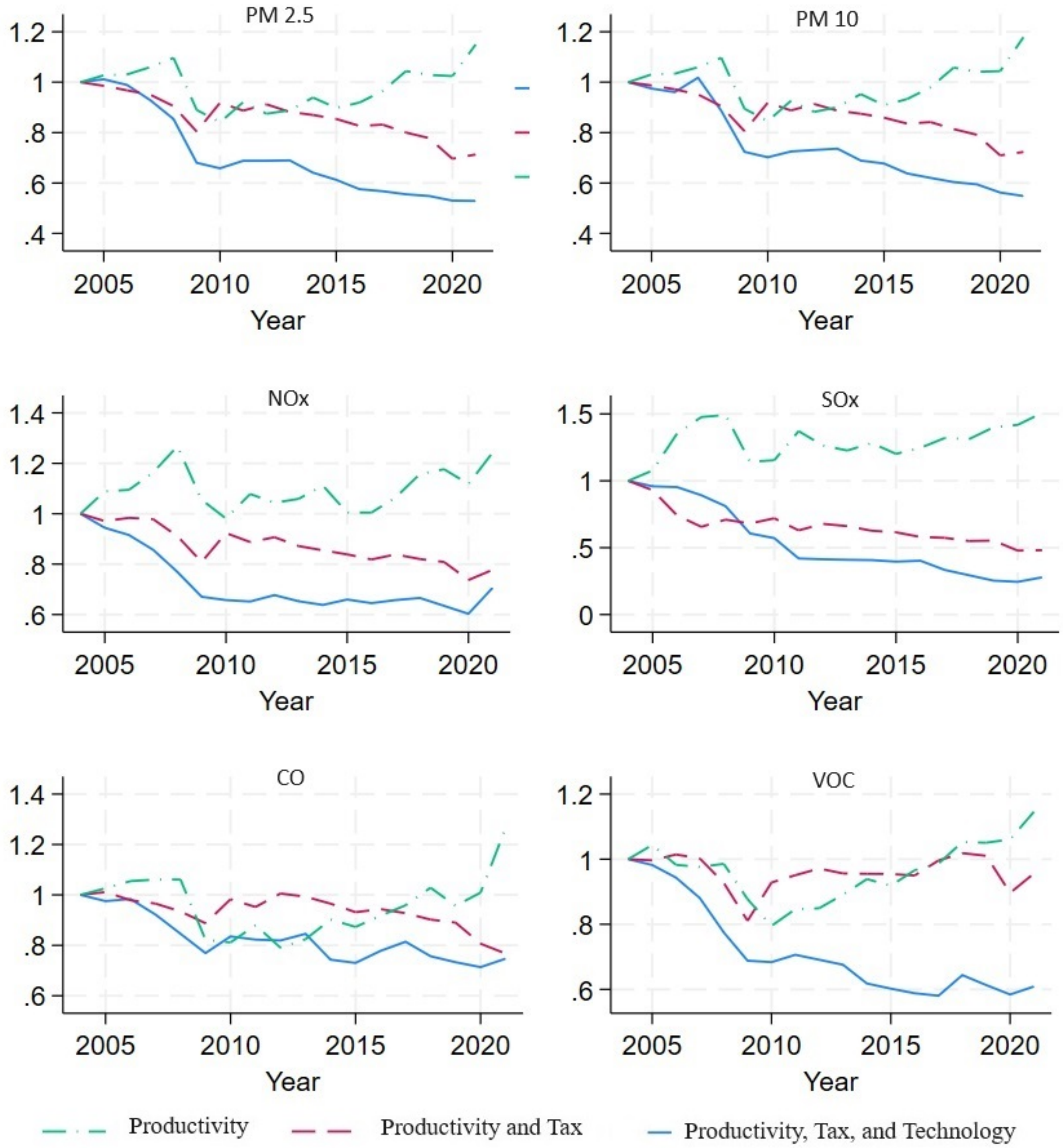
$$\{\hat{m}_s, \hat{t}_s, \hat{\gamma}_{R,s}/\hat{\gamma}_{Z,s}\} = \begin{cases} \{\hat{m}^*_s, 1, 1\} \\ \{\hat{m}^*_s, \hat{t}^*_s, 1\} \\ \{\hat{m}^*_s, \hat{t}^*_s, \hat{\gamma}^*_{R,s}/\hat{\gamma}^*_{Z,s}\} \end{cases} \tag{1.40}$$

The first row assesses how sector productivity shocks influenced pollution and output, with $\hat{m}_s$ adopting its historical value $\hat{m}^*_s$, while other shocks remained constant at their 2004 values. The second counterfactual gauges the environmental tax's effect on emissions and output, assuming a fixed 2004 technology composition for the sector without any subsequent technological shifts. Consequently, OAF and EAF remained unchanged from their 2004 levels. Finally, the third counterfactual evaluates the effect of environmental regulation on pollution emissions and output. The gap between the second and third scenarios illustrates the impact of technological changes in the sector on pollution emissions and output.

1.8.2 Counterfactual Analysis of Manufacturing Emissions

Figure 1.9 depicts the model's approach to decomposing manufacturing emissions. As an alternative viewpoint for the statistical decomposition approach discussed in section 1.2, the model attributes the historical trends in the aggregate emissions to productivity shocks, changes in environmental tax (primary regulation impact), and regulation-induced technological shifts within the sectors (secondary regulation impact).

Figure 1.9: Canada's Manufacturing Counterfactual Emissions Under Subset of Shocks, from 2004 to 2021, (2004=1)



Notes: This figure depicts the time trajectories of pollution emissions under three distinct counterfactuals. The solid (blue) line represents the actual historical pollution emissions, which include productivity, environmental tax, and technological shifts. In contrast, each dashed line illustrates the model's counterfactual prediction based on shocks following their historical paths and others remaining at 2004 levels. Data sources: ASM and NPRI.

Figure 1.9 demonstrates the time trajectories of manufacturing emissions in equation (1.33) under three distinct counterfactual scenarios, as presented in equation (1.40). The solid blue line represents the actual historical emissions, which include productivity, environmental tax, and technological shifts. In contrast, the dashed-dotted green line illustrates the model's counterfactual based on productivity shocks and others remaining at their 2004 levels. The dashed red line shows the counterfactual scenario based on changes in productivity and environmental tax, assuming that only the business-as-usual technologies in 2004 are available within the sectors.

The counterfactual analysis reveals that changes in sectors' productivity (i.e., the dashed-dotted green line) alone cannot fully account for the decline in manufacturing emissions. The gap between the blue and green lines represents the extent to which environmental regulations affect manufacturing emissions. Without the regulations that were put into place, the emissions levels for 2021 would have been significantly higher compared to the base year of 2004. For instance, pollutants such as PMs, NOx, VOC, and CO would have been 20% higher than their levels in 2004, hence much higher than their actual levels in 2021 (i.e., 65%, 50%, 55%, and 45%, respectively). Furthermore, the level of SOx would have been 50% more than its recorded level in 2004 and 80% above the actual 2021 level.

The overall impact of environmental regulations on emission levels is broken down into primary and secondary regulation effects. The gaps between the dashed red and dashed-dotted green lines highlight the primary impact of regulations on emissions. Except for VOC, much of the reduction in emissions resulted from primary regulation impacts, which are costly changes associated with changes in relative prices and subsequent reallocation of output across sectors.

I provide three main observations from the figure:

Observation A: Except for VOC and depending on the pollutant, the primary regulation effect had a significant impact on reducing emissions, accounting for 70% to 90% of the reduction, as indicated by the ratio between the distance of the red and green lines compared to the distance of the blue and green lines in 2021.

Observation B: Since 2012, there has been an overall increase in the impact of primary regulations following more stringent environmental regulations. The green lines have risen while the red lines have declined, indicating the increasing importance of the primary impact of regulations.

Observation C: The gaps between the red and blue lines indicate the remaining discrepancies and emphasize the role of secondary regulation impacts. These impacts arise from technological changes within a sector due to regulations. They help to offset some of the costly reductions in emissions brought about by lowering output.

The decreasing secondary regulation effects from 2012 can be attributed to the diminishing opportunities to further reduce emissions by employing cleaner and more efficient abatement technologies.

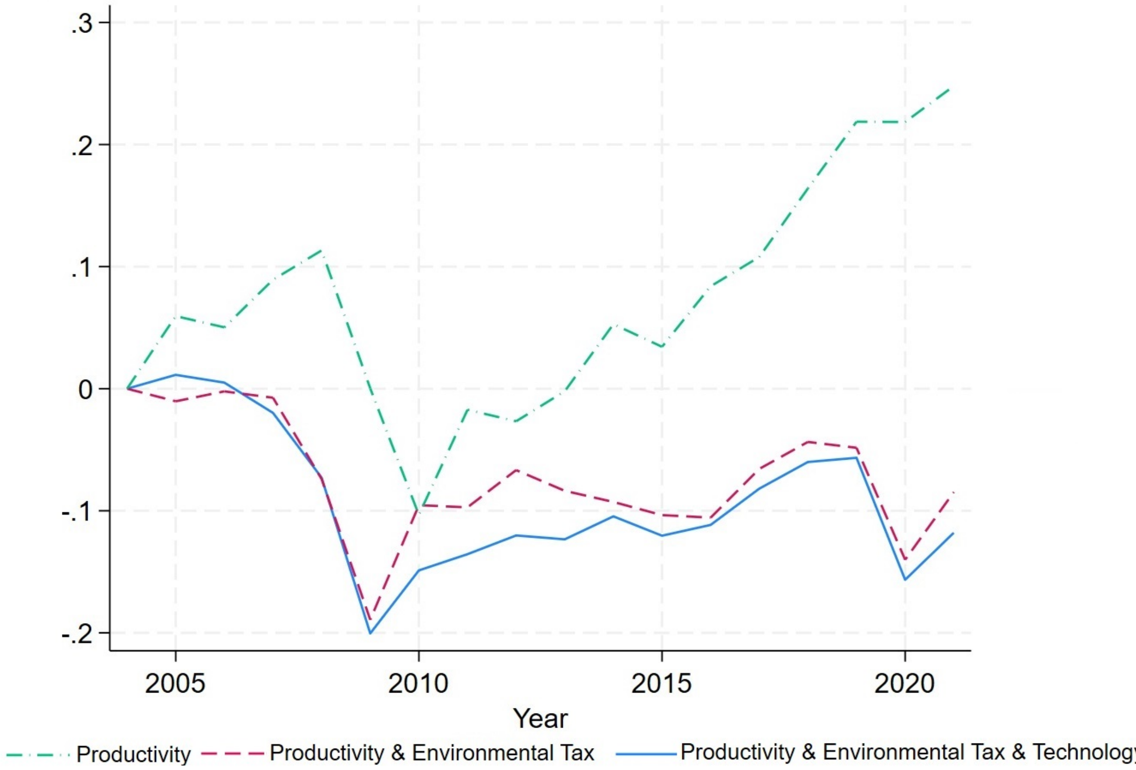
1.8.3 Counterfactual Analysis of Manufacturing Output

Figure 1.10 depicts the time trajectories of the manufacturing output in equation (1.34) under three distinct counterfactual scenarios, as presented in equation (1.40)[29] Considering all shocks, including sector productivity, environmental taxes, and technological shifts, the solid line represents historical manufacturing output. The dash-dotted line represents the scale effect if only productivity shocks are considered. The dashed line represents the scale effect if both productivity and environmental tax shocks are considered.

The blue solid line in the graph shows how the aggregate output has changed over the period of 2004 to 2021. Manufacturing output has undergone three major periods during this time. First, there was a decline in output from the all-time peak in 2005 to the level of the financial

[29] As we discussed in Section 1.2, the changes in manufacturing output also represents scale effect. Without changes in production composition and techniques, emissions as production byproducts should follow the output ups and downs.

Figure 1.10: Counterfactual Manufacturing Output, 2004-2021, (2004=0)



Notes: The figure shows the changes in manufacturing output over time in three different scenarios. The solid line represents the actual historical scale effect, considering productivity, environmental taxes, and technological shifts. The dash-dotted line represents the scale effect if only productivity shocks are considered. The dashed line represents the scale effect if both productivity and environmental tax shocks are considered. Data sources: ASM and NPRI.

crisis in 2009. Second, there was a recovery in output from 2010 to 2019. Finally, there was an output shock due to COVID-19 in 2020, followed by the post-pandemic recovery in 2021. Overall, the output level in 2021 is almost 12% lower than it was in 2004.

I add three more observations to the previous observations from this figure:

Observation D: Figure 1.10 illustrates the significant impact of environmental regulations on manufacturing output. This impact is represented by the difference between the dash-dotted green line and the solid blue line. It indicates that manufacturing output would have been 35% higher without environmental regulations. Most of this reduction is attributed to the primary regulation effects, shown by the difference between the dash-dotted green and dashed red lines.

Observation E: The pattern that appears familiar from the previous analysis is the increasing effect of primary regulation post-2012, as shown by the diverging counterfactual lines - the dash-dotted green and dashed red lines.

Observation F: The overall secondary regulation effect on output is not considerable, but it helped to reduce the manufacturing output. Even when allowing for technologies that can mitigate output reduction, the overall effect of abatement technologies was to reduce output, which complements the conventional wisdom in the literature that abatement technologies tend to reduce firms' productivity and output.

In Appendix F, I have shown the counterfactual analysis of the composition and the technique effect observed in the data discussed in Section 1.2.

1.9 Conclusion

Over the last twenty years, the Canadian manufacturing sector has seen an average 40% decline in emissions despite an increase in real output since 2009. This reduction is mainly due to a decrease in the sector's emission intensity, which results from changes in production techniques brought about by regulations.

My study introduces a model delineating the nexus between firm production decisions and environmental regulations. Within this framework, regulated firms navigate a range of abatement technologies, some of which simultaneously reduce emissions and boost productivity. The model separates two core effects of environmental regulations: the "primary regulation effect," in which higher taxes increase the average cost of production and the relative sales prices within the regulated sectors and tend to decrease the sector output, output share, and thus emissions.

The "secondary regulation effect" stems from the regulation-induced technological shifts within sectors. Facing a higher cost of production, some of the lowest-productivity firms decide to exit the market; some low-productivity firms keep on using business as usual; other higher-productivity firms choose technologies that may reduce their productivity; the highest group of firms may adopt clean technologies that may boost their productivity. The technological shifts within the sectors tend to offset some of the reductions in sector output brought about by the primary regulation effect. They also largely reduce the sector emissions.

This study delved into the intricate dynamics of primary and secondary regulation effects on manufacturing emissions and output. Based on empirical observations from counterfactual scenarios and statistical decomposition findings, the analysis sheds light on these regulatory mechanisms' pivotal role in shaping environmental outcomes.

This study underscores the significance of primary regulation effects in driving reductions in manufacturing emissions. These effects, primarily stemming from changes in relative prices and output reallocation across sectors, have been found to account for a substantial portion of emission reductions, ranging from 70% to 90%, with exceptions noted for certain pollutants.

Notably, our findings reveal an increasing importance of primary regulation effects versus the secondary effects post-2012, reflecting the impact of stricter environmental policies on emission abatement efforts and diminishing opportunities to further reduce emissions by using better abatement technologies.

This study also underscores the substantial impact of environmental regulations on manufacturing output, emphasizing the pivotal role of primary regulation effects in driving a 35% reduction in output.

As policymakers navigate environmental governance challenges, understanding the nuanced interplay between these regulatory mechanisms will be crucial for achieving sustainable environmental outcomes in the manufacturing sector.

1.9.1 Assessing Porter's Hypothesis

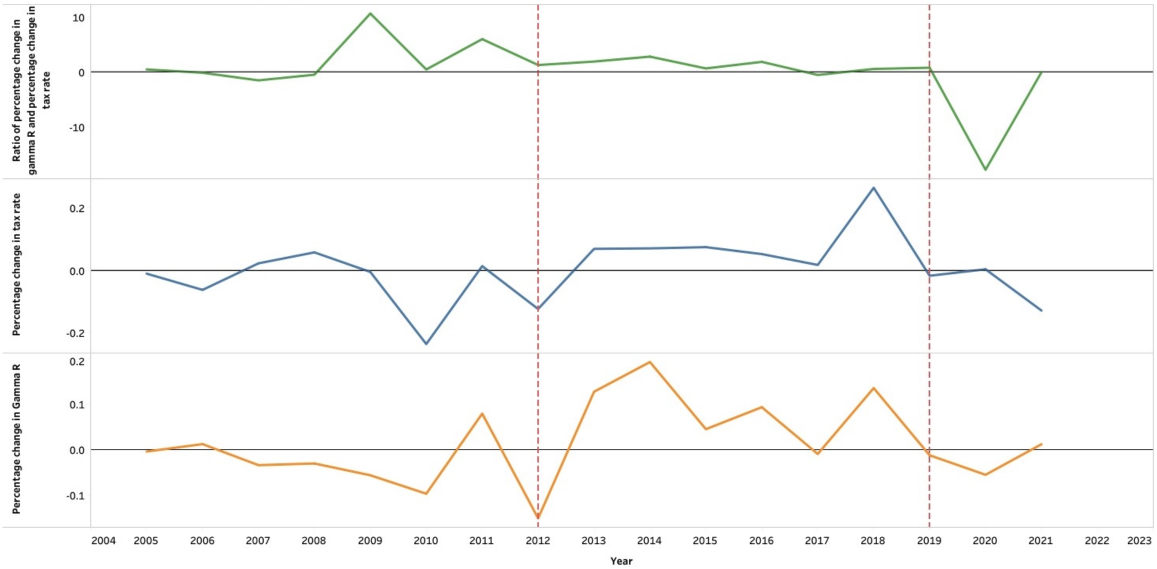
I have already established that the sector's OAF, $\gamma_{R,s}$, is increasing in environmental taxes, t. Also, from equation (1.34), proportional changes in output are related to $\gamma_{R,s}^{1/\theta_s}/t_s$. If in any year, within any regulated sector, there is a positive change in tax, t_s, and simultaneously, $\gamma_{R,s}^{1/\theta_s}$ grows faster than that, that means the sector output has increased as a result of a higher tax rate, a piece of evidence for strong Porter's hypothesis.

I detect evidence for Porter's hypothesis in several regulated sectors in this paper. Figure 1.11 shows percentage change in $\gamma_{R,s}^{1/\theta_s}$ (the bottom panel), percentage change in t_s (the middle panel), and percentage change in $\gamma_{R,s}^{1/\theta_s}/t_s$ (the top panel). Between 2012 and 2019, a continuous positive change in implied environmental tax resulted in positive changes in output, which suggests Porter's hypothesis.

I have already established that the sector's Outcome Adjustment Factor (OAF), $\gamma_{R,s}$, increases with environmental taxes, denoted as t. Furthermore, from equation (1.34), it is clear that proportional changes in output are directly related to the ratio $\gamma_{R,s}^{1/\theta_s}/t_s$. Consequently, if in any given year, within a regulated sector, there is a tax increase, t_s, and $\gamma_{R,s}^{1/\theta_s}$ grows at a faster rate, this indicates an increase in sector output as a direct result of higher tax rates, providing evidence in support of Porter's hypothesis.

In this paper, I find evidence supporting Porter's hypothesis across several regulated sectors. Figure 1.11 illustrates the percentage changes in $\gamma_{R,s}^{1/\theta_s}$ (bottom panel), t_s (middle panel), and percentage changes in sector output (top panel). Between 2012 and 2019, continuous positive changes in the implied environmental tax coincided with positive changes in output, confirming Porter's hypothesis. (I refer the reader to Appendix J for more evidence on Porter's hypothesis.)

Figure 1.11: Evidence for Porter's hypothesis in Pulp, paper, and paper board mills (3221), (2004=0)



Notes: The figure shows that the sector output has increased due to increased implied environmental tax between 2012 and 2019.

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Chapter 2

2 The Impact of Cloud Seeding on Hail Damage

A Ten-Year Dynamic Panel Data Analysis of Hailstorm Suppression Program in Alberta

2.1 Introduction

Hailstorms are significant and destructive meteorological events that can substantially affect agricultural and critical infrastructure in communities, particularly in Alberta, Canada, where the frequency and intensity of these events rank among the highest in North America. The region known as ”Hail Alley,” extending from Calgary to Red Deer, experiences a disproportionately high volume of hail incidents, leading to significant economic losses.

The steady increase in annual losses and loss intensity over the years underscores the growing challenge of mitigating hailstorm-related damages in Alberta (Insurance Bureau of Canada, 2023). Between 1981 and 1998, thirteen storm events led to accumulated property damages amounting to $600 million in Calgary. In 1996, Alberta faced two hailstorms that caused a $103 million loss. In 2010, a hailstorm with golf ball-sized hailstones led to over $400 million in property damage in Calgary. In 2012, another hailstorm in Calgary caused $552 million in damage, almost half the $1.2 billion in claims across Canada (Desjardins Insurance, 2017). A hailstorm in 2020 resulted in at least $1.2 billion in insured damages. This event was triggered by tennis ball-sized hailstones, extreme wind gusts averaging 72.4 km/hr, and 54.1 mm of precipitation, as measured in Calgary (Rieger, 2020).

To mitigate hailstorm damages in Alberta, the Alberta Hail Suppression Program (AHSP) was Initiated in 1996. The program, overseen by Weather Modification, Inc., operates annually from June to mid-September, focusing on protecting urban areas. Their methods include cloud seeding, where silver iodide particles are dispersed into storm clouds to alter hail formation processes, aiming to reduce hailstone size and frequency.

Despite being practiced for a long time, the efficacy and economic justification of cloud seeding remain subjects of active research and debate (Knowles and Skidmore, 2021;Gilbert et al., 2016). This study aims to develop a statistical methodology to measure the effectiveness of cloud seeding using radar data and further estimate the impact of cloud seeding on hail damage to autos and properties in Calgary, Alberta.

Some studies investigating the economic aspects of hail suppression through cloud seeding have focused on indirect effects, such as the potential increase in precipitation and its subsequent impact on crop yields (e.g., Swanson et al., 1972; Knowles and Skidmore, 2021). These analyses typically compare regions that employ cloud seeding techniques to those that do not. However, the indirect effect analysis often requires addressing difficult issues such as potential selection bias, wherein regions selected for cloud seeding may inherently experience higher rates of precipitation and hail occurrences or spillover effects, which may skew the results and lead to inaccurate conclusions about the efficacy of cloud seeding as a method for hail suppression.

In contrast, some studies directly address the effect of cloud seeding on hail suppression and damage (Wieringa and Holleman, 2006; Dessens et al., 2016; Gilbert et al., 2016; and Pirani et al., 2023). Dessens et al. [2016] reviewed historic and contemporary silver iodide cloud seeding projects using ground generators in Switzerland, Argentina, North America, France, and Spain. The study used physical measurements, meteorological observations, and simulations to evaluate hail damage reduction. Results showed variable success, with significant reductions in some cases, largely depending on the positioning and operation of generators. A major limitation was the difficulty in conclusively quantifying effectiveness due to the complexity of weather systems and the short duration of many projects.

In Alberta's Hail Alley, Gilbert et al. [2016] examined and compared three severe storms that occurred very close in space and time on July 21, 2015. Using the radar data, two seeded and one unseeded storms were compared. The study found that seeded storms had smaller coverage areas and less intensity, that is, less maximum reflectivity and less Vertically Integrated Liquid (VIL) compared to the unseeded ones[1].

Pirani et al. [2023] expanded the analysis by including radar-derived metrics from 187 simple storm tracks having above an hour life cycle spanning from 2011 to 2020. They chose VIL and hail mean coverage area as proxies for hail damage potential and compared storm characteristics before, during, and after seeding. Their results showed that in nearly 60% of cases, seeded scans had lower median VIL and mean area values than unseeded portions, with more pronounced effects 30 minutes post-seeding. They used Mann-Whitney and Wilcoxon's tests to confirm these differences as significant. They concluded by recommending using numerical models that account for storm dynamics and characteristics to analyze a wide range of storms over time simultaneously.

We propose a dynamic panel data model for a storm's VIL evolution and seeding impact to address Pirani et al. [2023]'s call for methods that simultaneously analyze a wide range of storms over time while accounting for storm dynamics and characteristics. Dynamic panel data analysis provides a robust framework for quantifying cloud seeding effects by enabling the exploration of changes in storm characteristics over time and across numerous storm tracks. Unlike time series or event analysis methods, which may focus on single dimensions or isolate specific events, dynamic panel data analysis manages the complexity of weather systems, where storm characteristics evolve rapidly and depend on various observed and unobserved factors.

We combine this model with radar-derived metrics from 187 seeded storm tracks in the Hail

[1] VIL measures the total water content in a cloud column and has been empirically linked to hailstone size and potential damage (Gilbert et al., 2016), or high radar reflectivity, particularly readings above 55 dBZ, often indicates the presence of large hailstones capable of causing significant damage (Amburn and Wolf, 1997). Reducing these radar-derived metrics following seeding activities is thus used as a proxy for the cloud siding effectiveness in mitigating hail damage (Pirani et al., 2023).

Alley, each with a life cycle of over an hour from 2011 to 2020. We estimate the impact of cloud seeding on radar-measured storm VIL and coverage area using system Generalized Method of Moments (System GMM) estimators developed by Blundell and Bond [1998]. These two variables serve as proxies for storm intensity and hailstone sizes.

Since we only observe seeded storms, we simulate a counterfactual scenario assuming the same storms were not seeded. Following the steps outlined by Porter [2022] and Porter [2023], we compare these simulated unseeded storms' VIL and coverage area with the observed seeded storms. This comparison allows us to estimate the potential reductions in hailstone sizes and storm intensities and, consequently, the savings in hailstorm damage costs to automobiles and properties in Calgary, Alberta, attributable to cloud seeding.

The results indicate that storm VIL is largely non-stationary and follows an autoregressive (i.e., AR(3)) pattern. It suggests that VIL size is heavily influenced by its recent past values, with diminishing influence over time. The impact of cloud seeding on VIL size varies across different quartiles of VIL. Cloud seeding significantly reduces VIL by approximately 16.3% in the first quartile of storm VIL sizes, about 8.8% in the second quartile, and is not statistically significant in the third quartile. In the fourth quartile, close to the maximum VIL, cloud seeding increases VIL by about 6%. These effects are immediate and diminish over time due to VIL's AR(3) process.

The overall effect of cloud seeding on average and maximum VIL distribution, which are proxies for the actual distribution of hailstone size, hit rate, and duration of hailstorms, depends on the frequency of seeding and the proximity of the seeding to the storm's maximum VIL. The simulation results indicate that the current seeding method is more likely to increase storms' average and maximum VIL size by 1% and 1.5%, respectively, leaving a negligible saving in hailstorm damage costs.

We recommend adjusting the cloud seeding method to achieve greater savings in hailstorm damages. Specifically, the policy suggests avoiding seeding storms as they intensify and approach their peak, particularly in the fourth quartile of VIL. Implementing this policy can slightly reduce the average and maximum VIL and, more importantly, eliminate the likelihood of adverse impacts of cloud seeding on storms' maximum VIL. This adjustment can result in an estimated annual savings of 14.3 million CAD in roof damages and 9.1 million CAD in auto repair damages in Calgary alone.

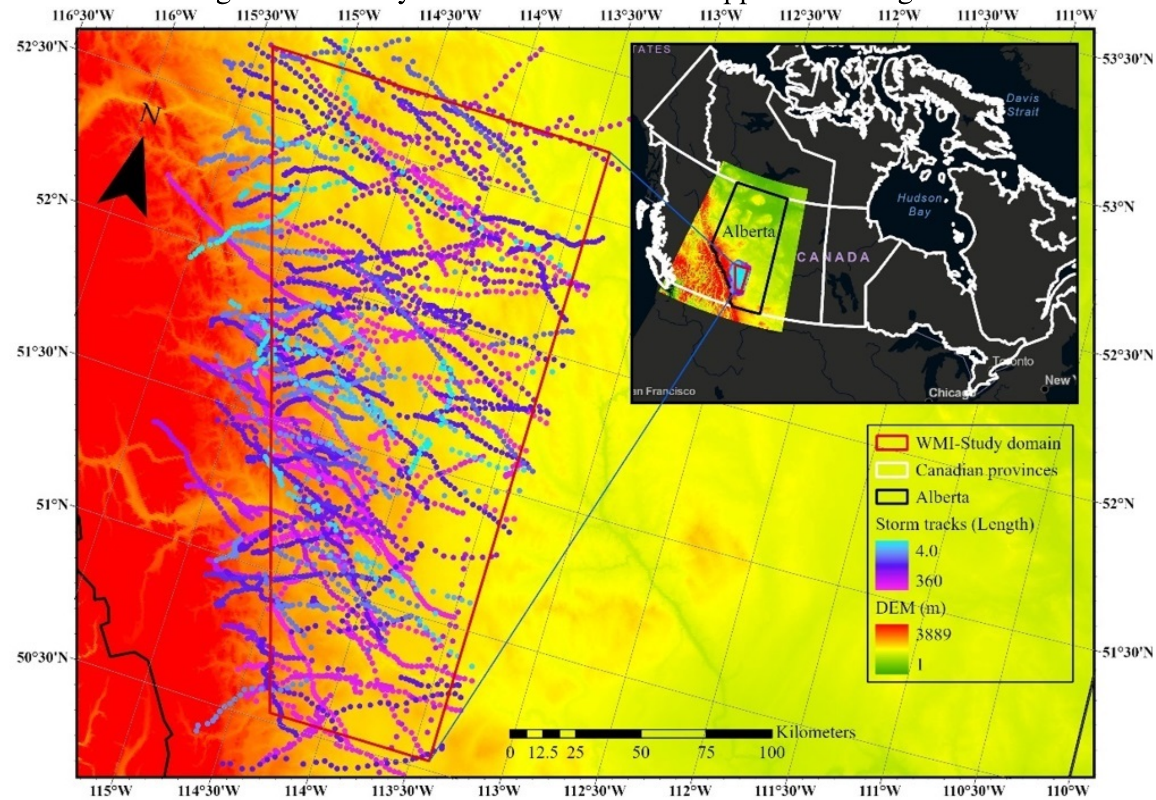
In the remainder of this paper, we introduce Alberta's study area and hail suppression program in Section 2. Section 3 describes the data used in the study. Sections 4 and 5 discuss the model and estimation method. Estimation results and discussions are presented in Section 6. Section 7 analyzes the effect of cloud seeding on hailstorm damage, and Section 8 concludes.

2.2 Study Area and Data

Calgary, situated in southern Alberta, is positioned in the core of Alberta's notorious "hail alley," an area east of the Rocky Mountains recognized for frequent hailstorms that can inflict significant damage on properties and infrastructure (Gilbert et al., 2016). In response to these destructive hail events, the insurance industry initiated an operational hail suppression seeding program in Alberta in 1996 through the Alberta Severe Weather Management Society (ASWMS), a consortium of insurance companies Krauss and Renick [1997]. Weather Modification Inc. (WMI) was contracted to execute the cloud seeding program Gilbert et al. [2016]. The project aimed to provide hail suppression services to protect urban areas in the hail alley (Figure 2.1).

The project initiates with a daily hailstorm threat forecast, categorized using the Convective Day Category (CDC) index, which evaluates the potential for thunderstorm activity, hail size, and the probability of seeding operations Gilbert et al. [2016]. Special attention is given to days with a CDC ranging from +2 (grape-sized hail) to +5 (greater than golf ball-sized hail). On these mission days, radar meteorologists guide pilots to the target

Figure 2.1: Study Area: Alberta's Hail Suppression Program



Notes: This figure shows the area of the hail suppression program in Alberta and the trace of 187 single storm tracks under study with over an hour life cycle spanning 2011 to 2020. The colors indicate the maximum VIL size of the storms.

storm locations for seeding operations. Five aircraft are used to disperse silver iodide into hailstorms, ceasing seeding when a storm cell no longer threatens urban areas Pirani et al. [2023].

This research analyzes radar-based data from 187 storms collected between 2011 and 2020. Each data point includes radar observations every four minutes, featuring three-dimensional reflectivity volume scans. Using TITAN software, thunderstorms are identified and tracked to form storm tracks. The software derives measures including storm size, location, intensity, track VIL, mean area coverage, top and base height, and average reflectivity. The selected storms are simple storm tracks with life cycles longer than one hour; the storms are not split or merged with others during their life cycle.

We followed Pirani et al. [2023] for this analysis to identify seeded and unseeded storm segments. The identification of seeded volumes is achieved through automated verification based on distance and time criteria to determine seeding events, which is combined with manual verification that involves aligning aircraft flight paths with radar-observed storm tracks.

The time required for seeding impacts to manifest can vary between 30 and 40 minutes (Gilbert et al., 2016;Pirani et al., 2023). This variance depends on the seeding technique used. Direct injection at the cloud's upper regions can yield faster results but requires more advanced and costlier aircraft capable of operating at higher altitudes. In contrast, base seeding involves releasing the seeding agent into the updraft beneath the cloud base, resulting in a longer time for the seeding effects to occur as the agent is transported upward Pirani et al. [2023]. In this study, we did not differentiate between these seeding methods; there is room for improving the analysis in this regard.

Table 2.1 illustrates descriptive statistics of storm tracks graded based on the CDC index. Our panel involves 187 simple storm tracks with at least a one-hour life cycle. The total observations include radar measures of 4381 volume scans. The most prolonged storm track in our sample was subjected to 60 volume scans, signifying its tracking span of 240 minutes. (I refer the reader to Appendix G for more information on descriptive statistics and the average pattern of storms' evolution classified based on the CDC index.)

Table 2.1: Descriptive Statistics of Storm Tracks by CDC Grade

CDC	**0**	**1**	**2**	**3**	**4**	**Total**
Maximum VIL Range (kg/m^2)	¡20	[20,30)	[30,70)	[70,100)	¿=100	**[2.4, 198]**
# of Storms	48	33	69	24	13	**187**
# of Observations	841	797	1752	669	322	**4381**
Average VIL (kg/m^2)	7.5	13.3	26.1	47.7	70.2	**25.2**
Ave. Life Cycle (# of Scans)	18	26.6	29.4	32.5	27.2	**23.4**
Ave. Life Cycle (minutes)	72	106.4	117.6	130	108.8	**93.6**

2.3 Methodology

2.3.1 Meteorological Background

We followed the steps of Gilbert et al., 2016 and Pirani et al. [2023] in defining the variables of interest and their definition of seeded/unseeded storms. For instance, VIL measures the total water content in a cloud column and has been empirically linked to hailstone size and potential damage (Gilbert et al., 2016), or high radar reflectivity, particularly readings above 55 dBZ, often indicates the presence of large hailstones capable of causing significant damage (Amburn and Wolf, 1997). Reducing these radar-derived metrics following seeding activities is thus used as a proxy for the cloud siding effectiveness in mitigating hail damage (Pirani et al., 2023).

Understanding these conditions and the strengths and limitations of radar metrics like VIL and reflectivity is crucial for optimizing cloud seeding strategies and improving predictive models used in hail suppression efforts. This knowledge helps refine intervention techniques to mitigate the damaging impacts of hailstorms more effectively.

The Vertical Integrated Liquid (VIL) is a critical metric in radar meteorology, representing the total mass of precipitation contained within a vertical column of the atmosphere above a unit surface area, typically expressed in kilograms per square meter (kg/m^2). The calculation of VIL involves integrating the liquid water content across the atmospheric column, utilizing radar reflectivity measurements at various vertical levels.

Reflectivities, represented by Z_i and Z_{i+1}, are the radar reflectivity values at consecutive vertical levels. These reflectivity measurements are crucial as they indicate the precipitation rate and type by quantifying the amount of radio energy reflected by precipitation particles. The mean reflectivity for a given layer, calculated as $\frac{Z_i+Z_{i+1}}{2}$, provides an averaged reflectivity value between two consecutive layers, offering a representative measure of reflectivity for the thickness of the layer between these two altitudes [Doviak, 2006].

The layer thickness, denoted by h, is the vertical distance between the two scanning levels, essential for representing the depth over which the average reflectivity is considered. The integration of the product of the mean reflectivity and the layer thickness across all layers from the ground to the top of the precipitation results in the Marshall and Palmer approximate VIL (Rose and Troutman, 2009):

$$VIL = \sum_{i=0}^{i=i_{max}} 3.44 \times 10^{-34} \left(\frac{Z_i + Z_{i+1}}{2} \right)^{4/7} dh \tag{2.1}$$

This formula sums the water content in each atmospheric layer, providing insights into the potential severity of precipitation events.[2]

2.3.2 Statistical Model

The correct application of these measurements within their meteorological context is essential for VIL computation [Fulton et al., 1998]. This study analyzes and compares the effectiveness of cloud seeding using two different model specifications. The first model includes all three variables that explain VIL, namely, the average reflexivity between radar-measured top,$\bar{Z}$, the storm's top height, h_{top}, and the storm's base height, h_{base}, separately in the right-hand side of the equation.

The second specification assumes a uniform distribution of reflectivities between scanning levels. It uses the following constrained variable, which summarizes the above three radar

[2] The primary advantage of using VIL and high reflectivity measures is their ability to provide rapid, real-time data on storm characteristics, which is crucial for the timing of cloud seeding operations. However, there are also drawbacks to consider. VIL, while useful, can sometimes provide misleading signals if the vertical extent of the storm is not substantial, as it integrates the liquid content throughout the cloud's entire height. As for reflectivity, while values above 55 dBZ are strong indicators of large hail, they do not account for all factors influencing hail size, such as wind shear and atmospheric stability, which might lead to either an underestimation or overestimation of hail potential. Additionally, radar measurements can be influenced by the distance from the radar and beam elevation angles, potentially affecting data accuracy in estimating hail size Pirani et al. [2023].

data into one variable on the right-hand side of the equation:

$$W = \bar{Z}(h_{top} - h_{base}) \tag{2.2}$$

Our panel dataset is based on a sample of 187 simple storm tracks with over an hour life cycle; that is, each storm track includes information from at least 15 volume scans. The panel is unbalanced, with some storm tracks having more observations than others. We expect VIL to adjust to changes in the above factors and cloud seeding with delay and the impact on VIL not decaying, at least for a few periods. The process of adjustments to changes in these factors may depend on the passage of time, which argues for a dynamic model in which lags of the VIL are also regressors. Thus, we utilize a dynamic model in which all variables are in logarithms as follows:

$$y_{it} = \alpha_1 y_{it-1} + \cdots + \alpha_p y_{it-p} + X'_{it}\beta + D_{it-8}\delta + u_i + \epsilon_{it}, \tag{2.3}$$

where

- y_{it} is the log VIL for storm i at time t with 4-minute intervals,
- $y_{it-1}, \ldots, y_{it-p}$ are the lagged values of log VIL, capturing the persistence and temporal dynamics in the data. This study uses $p = 3$ lags to control the auto-correlation in errors and to deal with the non-stationarity of log VIL,
- $\alpha_1, ..., \alpha_p$ are the first- to Pth-order auto-correlation,
- X'_{it} is a vector of explanatory variables which, depending on model specification, may include log $\bar{Z}$, log h_{top}, log h_{base}, log W and the vector of ones to account for the intercept in the model,
- D_{it-8} is a dummy variable indicating the occurrence of cloud seeding 8 periods prior, and it is zero otherwise,

- u_i are individual fixed effects accounting for unobserved heterogeneity across storms; for instance, they can represent any initial weather forecast characteristics that qualify a coming storm for cloud seeding,
- ϵ_{it} is the idiosyncratic error term.

2.3.3 Estimation Method

A naive attempt to estimate the equation (2.3) is to regress the dependent variable on the explanatory variables using the Ordinary Least Squares (OLS) estimator. An immediate problem in applying OLS is that potentially $y_{it-1}, ..., y_{it-p}$ may be correlated with the fixed effects, u_i, which may give rise to dynamic panel bias, which violates an assumption necessary for the consistency of OLS (Nickell, 1981). The large life cycle of the selected storms would dwindle this endogeneity problem; however, the highly persistent VIL process (i.e., α_1 close to 1) works in the opposite direction.

One way to estimate the model specified in equation 2.3 is first-difference transform to eliminate the fixed effects [3] :

$$\Delta y_{it} = \alpha_1 \Delta y_{it-1} + ... + \alpha_p \Delta y_{it-p} + \Delta X'_{it} \beta + \Delta D_{it-8} \delta + \Delta \epsilon_{it}, \tag{2.4}$$

where $\Delta y_{it} = y_{it} - y_{it-1}$. By first-difference transformation, we eliminate the fixed effects, but y_{it-1} in $\Delta y_{it} = y_{it} - y_{it-1}$ can be correlated with ϵ_{it} in $\Delta \epsilon_{it} = \epsilon_{it} - \epsilon_{it-1}$. Meanwhile, deeper lagged dependent variables such as y_{it-p-1} or y_{it-p-2} are not correlated with $\Delta \epsilon_{it}$ as long as ϵ_{it} are not serially correlated. Thus, they can be used as instruments.

Similarly, any predetermined explanatory variables in X_{it} that are not strictly exogenous become potentially endogenous because they may also be related to ϵ_{it}. However, deeper lags of the regressors, such as X_{it-1}or X_{it-2}, remain uncorrelated to the errors and are available

[3] Roodman, 2009 discuss another way to deal with the dynamic bias problem, namely using least-squares dummy-variables (LSDV) estimator and explains the problems that may arise using LSDV.

as instruments.

One way to incorporate deeper lagged dependant and explanatory variables as instruments is with two-stage-least squares ($2SLS$) difference and level estimators (Anderson and Hsiao, 1982). Similarly, Arellano-Bond's Generalized Method of Moments (GMM) estimator (AB) uses deeper-lagged dependent variables and regressors as instruments to improve the efficiency of estimates for the first-difference model[4].

Arellano and Bond [1991] show that compared to OLS, $2SLS$ difference, and level estimators, difference GMM exhibits the least bias and variance in estimating the parameters of interests. Blundell and Bond [1998] demonstrates that if the dependent y is close to random walk, that is to say, α_1 in equation 2.4 is close to 1, then the difference GMM estimator performs poorly because past levels provide little information about the future changes, thus, lagged level variables are week instruments for first-difference variables.

Blundell and Bond [1998] develops a System GMM estimator that combines equations in differences with equations in levels. This approach uses lagged levels as instruments for the difference equations to control for fixed effects. It also uses lagged differences as instruments for the equations in levels to enhance the strength and relevance of the instruments, particularly when dealing close to random walk processes. Using a difference GMM estimator can be problematic since all the weather variables, including VIL and the explanatory variables, are close to a random walk with α_1 close to 1. This is an issue in meteorological processes where unit roots are typically present, leading to explosive changes in the short-term trends.

The system GMM estimator embodies the following assumptions about the data-generating process (Roodman, 2009):

[4]The first difference equation can be written as: $\Delta y = \Delta R\pi + \Delta u$.Then, apply GMM estimator: $\pi = [\Delta R'Z(Z'\Omega Z)^{-1}Z'\Delta R]^{-1}\Delta R'Z(Z'\Omega Z)^{-1}Z'\Delta y$ where Z is the instrument matrix for ΔR. The matrix Ω can be estimated from the variance of the error terms using the Arellano-Bond estimator.

- Error terms have zero conditional mean (i.e., $E[\epsilon_{it}|X_i, D_i] = 0$),
- No serial correlation in errors (i.e., $E[\epsilon_{it}\epsilon_{is}|X_i, D_i] = 0$ for $s \geq 0$),
- Fixed effects are statistically independent of the errors (i.e., $u_i \perp\!\!\!\perp \epsilon_{it}$) and may be arbitrarily distributed,
- There is a constant correlation between regressors and the fixed effects (i.e., $E[X_{it}u_i] = E[X_{is}u_i]$ for all $s \geq 0$). For instance, initial forecasts are informative about the realization of the storms, and the relation between these variables and initial forecasts does not change over time.
- Regressors can be endogenous or predetermined, that is, independent of the current disturbances, they can be influenced by past ones (i.e., $E[X_{it-s}\epsilon_{it}] = 0$).
- The dependent variable is stationary.

We perform diagnostic tests to validate the robustness and reliability of the system estimator to estimate the model. These tests ensure the integrity of the model's assumptions and the validity of the instrumental variables used:

- The Fisher-type unit-root tests utilizing Phillips-Perron (PP) and Augmented-Dicky-Fuller (ADF) test adjustments to determine the presence of unit roots in the panels under investigation,
- AR(1) and AR(2) tests to check for autocorrelation in the residuals of the model,
- Hansen's test of overidentification to examine the overall validity of the instruments used in the estimation process,

2.4 Results and Discussion

2.4.1 System GMM Estimation Results

Table 2.2 shows the Fisher-type unit-root test, utilizing Phillips-Perron (PP) and Augmented-Dicky-Fuller (ADF) test adjustments for the variables used in the model. Except for $Log(h_{top})$ the results show that based on the PP test, there is sufficient evidence to reject the null hypothesis that all panels are non-stationary. Also, Except for $Log(\bar{Z})$ the results show that based on the ADF test, there is insufficient evidence to reject the null that all panels are non-stationary. The test results raise concerns about the non-stationarity of the dependent variable, Log(VIL). We must refer to the estimation results in the level system GMM estimates to determine whether the dependent variable is non-stationary. Table 2.3

Table 2.2: Fisher-type Unit-root Test Results

Variables	**lags**	**PP**	**ADF**
$Log(VIL)$	3	Accept	Fail
$Log(W)$	3	Accept	Fail
$Log(\bar{Z})$	1	Accept	Accept
$Log(h_{top})$	3	Fail	Fail
$Log(h_{base})$	1	Accept	Fail

Notes: The Fisher-type unit-root test, utilizing Phillips-Perron (PP) and Augmented Dicky-Fuller (ADF) test adjustments, are reported for main variables.

presents the results of the system GMM estimators to measure the impact of cloud-seeding on the log(VIL). The analysis encompasses two model specifications: Column (1) details the results from the first model specification incorporating the natural logs of three variables, $\bar{Z}$, h_{top}, and h_{base}, as independent variables, and column (2) presents the outcomes from the second model specification which includes the log(W) as the independent variable.

Both models include intercept terms and three levels of lagged dependent variables to meet the $AR(2)$ condition, ensuring no second-order serial correlation of errors exists. The variable seeding dummy, D_{it-8}, is set to 1 if the volume scan was seeded 8 periods (32 minutes) prior and zero otherwise. In both model specifications, the results show a statistically sig-

Table 2.3: The Effect of Seeding on VIL - System GMM Results

Variables	**(1)**	**(2)**
1st Lag	0.59	0.84
	(0.00)	(0.00)
2nd Lag	-0.17	-0.22
	(0.00)	(0.00)
3rd Lag	0.02	0.01
	(0.39)	(0.5)
Seeded	-0.031	-0.046
	(0.011)	(0.001)
AR(1)	0.00	0.00
AR(2)	0.59	0.26
Hansen test of overid. restrictions	0.51	0.51
GMM instruments for levels:		
- Hansen test excluding group	0.67	0.63
- Difference (null H = exogenous)	0.05	0.11
Instrumental variables		
- Hansen test excluding group	0.49	0.49
- Difference (null H = exogenous)	0.54	0.53

Notes: The dependent variable is log VIL. Three levels of lagged dependent variables and a seeding dummy were used. Column (1) is the results of the system GMM estimation of the first model specification, in which $\bar{Z}$, h_{top}, and h_{base} are separately on the right-hand side of the equation. Column (2) is the results of the system GMM estimation of the second model specification, which includes log (W). Two-step GMM and robust standard errors are reported. P-values for various tests are reported. The estimation results for other explanatory variables are not shown.

nificant impact of lagged dependent variables, confirming their importance in predicting log(VIL). The seeded dummy variable exhibits statistically significant negative coefficients for both specifications. That is, overall seeding tends to reduce the log(VIL).

The AR(1) test indicates the presence of first-order serial correlation, as expected in first-difference models. The AR(2) test results do not reject the null hypothesis that errors have no second-order serial correlation. Hansen's tests of over-identification restrictions provide p-values well above conventional significance levels, confirming that the instruments are valid and the model is not overfitted. This is further supported by additional Hansen tests for specific groups of instruments and the difference test results, which indicate that the null hypothesis of exogenous instruments cannot be rejected.

Similar results are driven by using alternative estimators to estimate the models in equations (2.3) and (2.4). Table 2.4 presents results from similar models using the previously discussed OLS, LSFE, and level and difference Instrumental Variable 2SLS estimators.

Compared to system GMM, OLS underestimates the seeding effect for both model specifications due to dynamic panel bias. The LSFE also underestimates the seeding effects, and it is less efficient. The level and difference of IV-2SLS estimated seeding effects are closer to system GMM results for the first specification but underestimated for the second model specification. Both estimators are less efficient than the system GMM.

Table 2.4: Estimation Results using alternative estimators

Variables	**(OLS)**	**(LSFE)**	**(IV-2SLS 1)**	**(IV-2SLS 2)**
Seeded - 1st spec.	-0.012	-0.010	-0.015	-0.027
	(0.17)	(0.24)	(0.24)	(0.38)
Seeded - 2nd spec.	-0.023	-0.015	-0.01	-0.01
	(0.07)	(0.23)	(0.61)	(0.058)

Notes: Results of 4 different estimators for each model specification. The dependent variable is log VIL. Three level-lagged dependent variables and a Seeded dummy were used.

2.4.2 Cloud Seeding and Proximity to Storms' Highest VILs

The question at hand is about the ideal timing of cloud seeding. Is it more effective to do so when the VIL sizes are closer to their peak or farther away from it? Studies have mixed opinions regarding the timing of seeding. For example, to increase the effectiveness of cloud seeding, Dessens et al. [2016] recommends starting cloud seeding at very early stages, long before the storm intensifies. In contrast, Pirani et al. [2023] implies that seeding would be more effective as a storm approaches its peak intensity.

We developed variables representing seeding at varying proximities to the storm's maximum Vertically Integrated Liquid (VIL) to address this question. Initially, we calculated the ratio of VIL to the maximum VIL for all storm tracks in each period. Following this, we segmented each storm track into quartiles based on these proximity values. Finally, we constructed new seeding dummy variables as interactions between D_{it-8} and the quartile dummies. The model is as follows:

$$y_{it} = \alpha_1 y_{it-1} + \alpha_2 y_{it-2} + \alpha_3 y_{it-3} + X'_{it}\beta + \sum_{k=1}^{4}(D_{it-8}.quartile_k)\delta_k + u_i + \epsilon_{it}, \qquad (2.5)$$

Table 2.5 presents the difference and system GMM estimates of the impact of seeding on log VIL based on proximity to storms' highest VILs. The results yield significant insights into the variable effects of cloud seeding across different stages:

- Seeding in the 1st quartile: A significant negative coefficient of -0.112 suggests that, on average, seeding a storm in stages far from its peak intensity reduces VIL size by 11.2%.
- Seeding in the 2nd quartile: On average, seeding a storm in the second quartile reduces VIL sizes by 7.1%.
- Seeding in the 3rd quartile: The coefficient for the third quartile is not statistically significant, indicating that, on average, seeding does not affect VIL sizes as the storm gets closer to its peak.
- Seeding in the 4th quartile: The fourth quartile shows a statistically significant positive coefficient of 0.058, suggesting that, on average, seeding storms at their peak

intensity increases the VIL size by 5.8%.

Table 2.5: The impact of seeding on VIL size across different storm stages

Variables	**1st Spec.**	**2nd Spec.**
Seeded - below 25% VIL size	-0.11	-0.16
	(0.00)	(0.00)
Seeded - 25% to 50% VIL size	-0.06	-0.09
	(0.00)	(0.00)
Seeded - 50% to 75% VIL size	0.01	0.03
	(0.35)	(0.17)
Seeded - above 75% VIL size	0.06	0.06
	(0.004)	(0.006)

Notes: Results of first difference system GMM estimators for each model specification. The dependent variable is log VIL. Three level lagged dependent variables and an interactive Seeded dummy with VIL quartiles were used.

These results suggest that the effectiveness of cloud seeding on VIL varies significantly depending on the proximity to the storm's maximum VIL. The negative effects in lower quartiles and the positive impact in the highest quartile could reflect varying physical dynamics in storms at different stages of development, which requires further research. These findings underline the importance of considering the intensity of storms when planning and executing cloud seeding operations.

2.4.3 Impulse Response Functions

Since the model is a dynamic model that includes the lagged dependent variables as explanatory variables, concluding the size of cloud seeding impact is complicated as the effect of seeding carries on for several periods and also, almost in all cases, cloud seeding frequently occurs over the life cycle of the storm.

To get some insight into the effect of seeding on VIL, we look into the impulse response functions of the model. Since the evolution of storms follows a variety of patterns, we define a storm that follows this pattern: The storm has a 28-period life cycle, with low intensity initially and gradually evolving to its maximum intensity between 16 to 18 periods before gradually cooling down afterward (see the details in Appendix I).

Next, we seed the storm by different methods and look at the percentage changes in the storm's VIL over time. We are looking to determine the impact of seeding on the maximum VIL, located between 16 and 18 periods.

Figure 2.2 demonstrates the impulse response functions (IRF) related to eight different seeding impulses:

- Graph 1 shows the IRF to an initial single seeding at time t=0. The effects on VIL appear in 8 periods, reducing the VIL size by 16%. The effect diminishes over 4 periods.
- Graph 2 shows the cumulative IRF to a series of seeding impulses from t=0 to t=3. The effects of frequent seeding in the first quartile compound to over 50% reduction in VIL before completely diminishing through the next few periods. The effect is not long-lasting enough to impact the maximum VIL between 16 to 18 periods.
- Graph 3 shows the cumulative IRF to a series of seeding impulses from t=0 to t=7. The effect of frequent seeding in the first and second quartiles compounds to over 50% reduction in VIL and a longer-lasting effect extending to the 16th period. The effect may potentially reduce the maximum VIL by 5%.
- Graph 4 shows the cumulative IRF to an extended series of seeding impulses from t=0 to t=10. The effect of frequent seeding through the first three quartiles compounds to over 50% reduction in VIL in early stages but can potentially increase the maximum VIL.
- Graphs 5 and 6 show the cumulative IRF to an extended series of seeding impulses from 0 to 13 and 0 to 16. The effects of continuous seeding through the highest storm intensity stages can potentially lead to a 15% increase in VIL size. That may

increase the maximum VIL of the storm, which correlates with larger hailstones and more hailstorm damage.

- Graphs 7 and 8 show the cumulative IRF to a series of seeding impulses through the entire storm life cycle, which tends to reduce storm VIL size.

2.4.4 Policy Recommendation

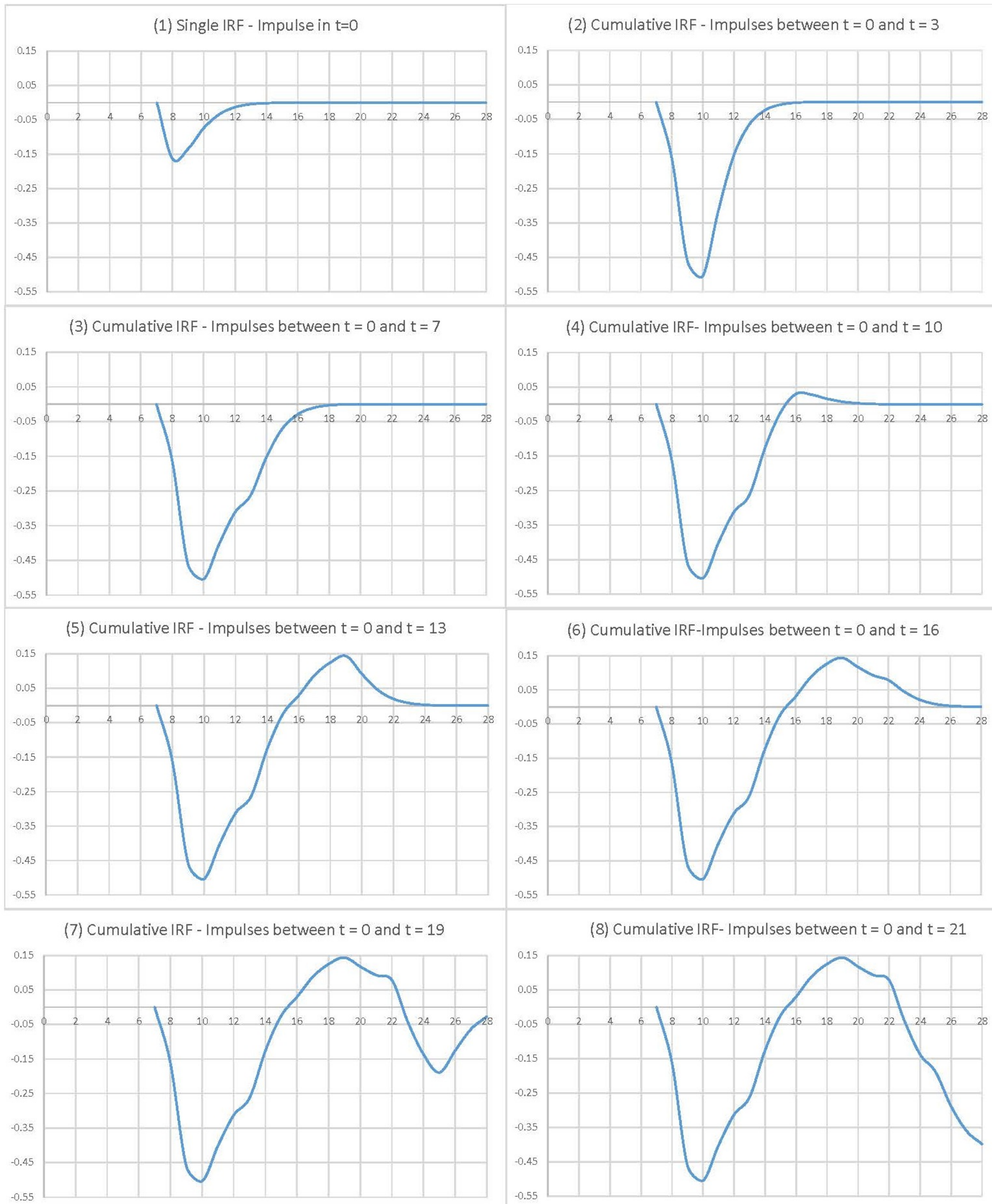
The IRFs shown in Figure 2.2 provide insight into how seeding a storm during its peak intensity may increase maximum VIL, eroding the seeding effect. In this section, we propose a modification to the seeding policy. We suggest not seeding the storms during their highest intensities. This potentially can increase the efficacy of seeding by avoiding increases in VIL sizes. Figure 2.3 shows the IRF of the modified seeding policy.

In the next section, we combine our estimated model with the observed storms in the data and conduct two simulations to construct unseeded storms and seeded storms under the modified policy in the counterfactual world. The counterfactual analysis estimates the cloud-seeding impacts on the average and maximum VIL distribution of storms, which eventually determine the potential savings in hailstorm damage.

2.4.5 Cloud Seeding and Mean Area of Hail Coverage

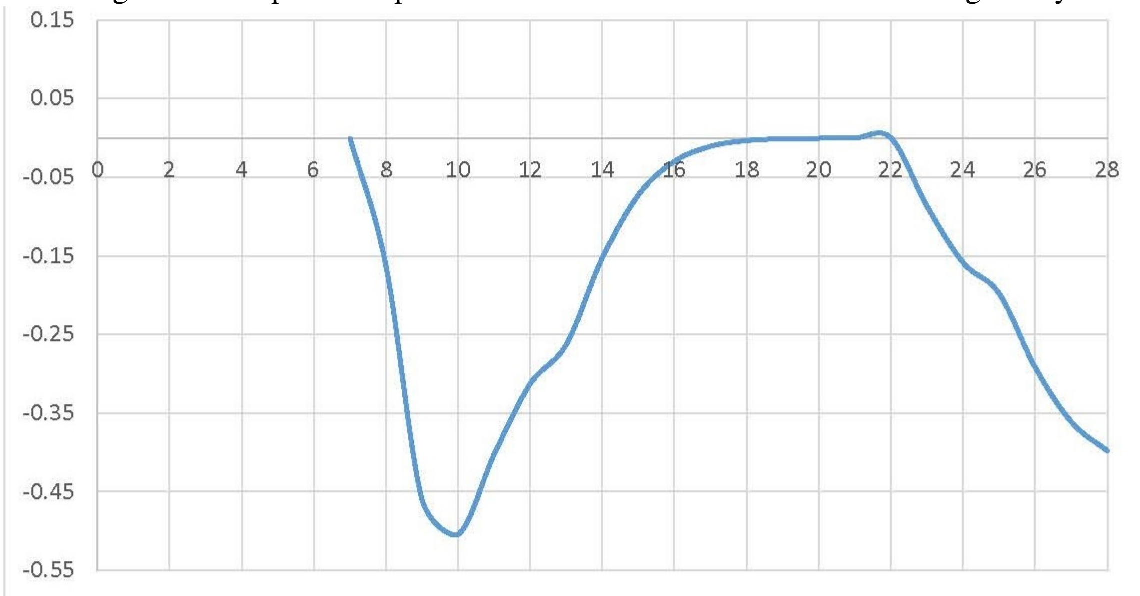
We also looked at the impact of seeding on the hail coverage area (defined as the mean area with reflectivity greater than 60 dBZ). We use a similar model structure in the equation (2.3) but use a radar-measure variable for the mean area with reflectivity greater than 60 dBZ as the dependent variable. Table 2.6 reports the results of system GMM estimations. The estimated seeding dummy coefficient is not statistically significant; that is to say, seeding has no clear impact on hail coverage area based on this model. Further research is required to choose appropriate explanatory variables for mean area coverage.

Figure 2.2: Impulse Response Functions (IRFs)



Notes: IRFs for a hypothetical storm shocked by different seeding methods.

Figure 2.3: Impulse Response Function of the Recommended Seeding Policy



Notes: IRF of a hypothetical storm shocked by the recommended seeding policy, in which the storm is not seeded in its peak intensity period.

2.5 Counterfactual Analysis

2.5.1 Methodology

The counterfactual analysis aims to compare the actual observed values of seeded storms' VIL with the predicted values under two hypothetical scenarios: Storms if they were not seeded (Unseeded Counterfactual) and storms if they were seeded under the recommended policy (Recommended policy counterfactual).

We are particularly interested in evaluating and comparing two values for the current and recommended seeding policies[5]: The ratio of the maximum VIL of seeded versus unseeded storms (F_{max}), and the ratio of average VIL of seeded versus unseeded storms (F_{mean}).

We use the Monte-Carlo simulation method to recover storms' VIL under unseeded and recommended policy counterfactual scenarios, following these steps:

[5] For more information about the current seeding policy see Appendix H

Table 2.6: The Effect of Seeding on Hail Coverage Area - System GMM Results

Variables	**(1)**	**(2)**
1st Lag	0.99	0.88
	(0.000)	(0.000)
2nd Lag	-0.18	-0.14
	(0.000)	(0.000)
Seeded	-0.021	-0.007
	(0.58)	(0.71)
AR(1)	0.000	0.000
AR(2)	0.90	0.52
Hansen test of overid. restrictions	0.6	0.77
GMM instruments for levels:		
- Hansen test excluding group	0.75	-
- Difference (null H = exogenous)	0.03	-
Instrumental variables		
- Hansen test excluding group	0.58	-
- Difference (null H = exogenous)	0.47	0.70

Notes: The dependent variable is the log mean area (km^2). Two level-lagged dependent variables and a Seeded dummy were used. Columns (1) and (2) are the results of the level and difference system GMM estimation where $\bar{Z}$, h_{top}, and h_{base}, are used on the right-hand side of the equation. Two-step GMM and robust standard errors are reported. P-values for various tests are reported.

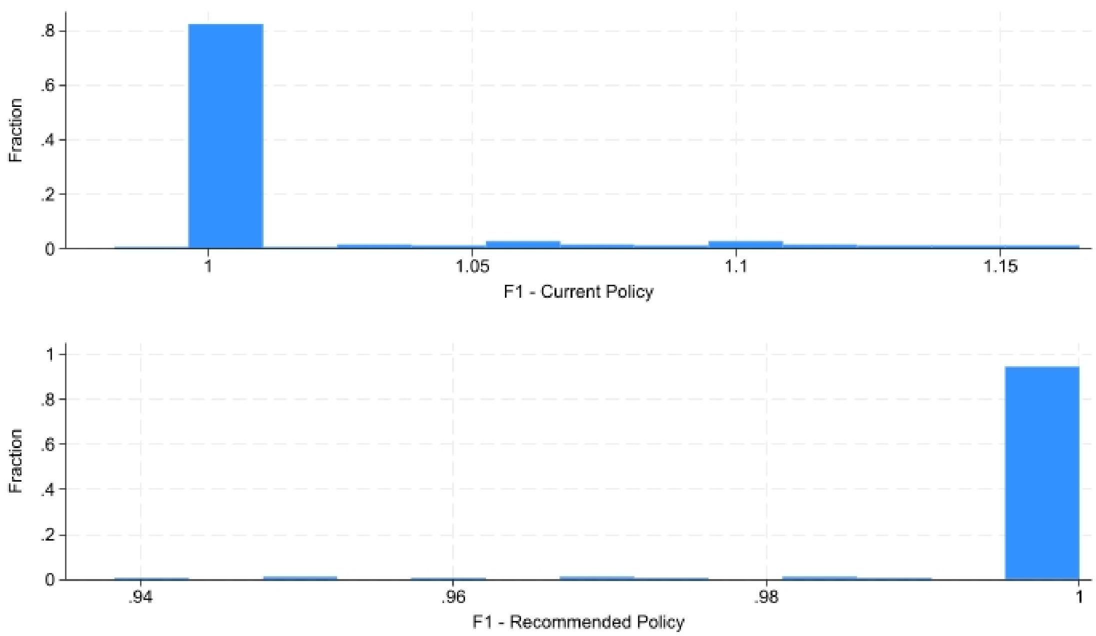
- Recover the residuals from the estimated model,
- Predict the values of VIL using the estimated model coefficients and the same values of explanatory variables and residuals,
- Set the seeding dummies equal to zero to predict the values of VIL under the unseeded counterfactual scenario.
- Set the seeding dummies in the third and fourth quartiles to zero in predicting values of VIL for the recommended policy counterfactual scenario.
- Calculate F_{max} and F_{mean} for the current and recommended policies.

2.5.2 Results

Figure 2.4 shows the probability distribution of calculated F_{max} for the current seeding policy (top) and the recommended policy (bottom). The top graph illustrates how the current seeding policy may increase the maximum VILs of some storms (cases with $F_{max} > 1$). Although these events have a very low probability, they can potentially lead to larger hailstorm damage relative to not seeding those storms at all.

In contrast, the bottom graph shows the advantage of the recommended policy to the current seeding method. The recommended policy eliminates the probability of an increase in maximum VILs due to cloud seeding. In all cases, we can see $F_{max} < 1$. Table 2.7 compares

Figure 2.4: Probability Distribution of F_{max} (The Ratio of seeded to unseeded Maximum VILs) - Current versus Recommended Seeding Policies



the calculated values of interest for current and recommended seeding policies. On average, the current seeding policy increases the maximum and average VILs by 1.5% and 1% compared to not seeding the storms at all, contributing to hail damages.

In contrast, the recommended seeding policy lowers both the average and maximum VILs ratio, leading to potential savings in hail damage.

Table 2.7: Counterfactual Analysis Results - Current versus Recommended Seeding Policies

Variable	Description of the Ratios	Current	Recommended
F_{max}	Maximum VIL	1.015	0.998
F_{mean}	Average VIL	1.010	0.999

2.6 Cloud Seeding and Hailstorm Damages

2.6.1 Methodology

To this point, we establish that cloud seeding has varying effects on the storms' VIL size, and the magnitude and direction of impacts depend on the proximity to maximum VIL when seeding occurs. We also recovered VIL sizes of the counterfactual unseeded storms and the seeded ones under the recommended policy.

In this section, we use the observed and counterfactual storms to estimate the economic impact of the hail suppression program in Calgary. First, we estimate the annual auto and property repair savings and the benefit-cost ratio of the current hail suppression program in Calgary. We then compare these values with the outcomes of the recommended policy.

We use the performance-based engineering approach to hail damage and loss estimation proposed by Porter [2022] and Porter [2023][6], which comprises the following steps:

- Estimate the storms' largest hailstone diameters for seeded, D_L, and unseeded storms, D'_L. Joe [2023] suggests that, on average, maximum VIL (kg/m^2) can be converted

[6] I am grateful to Keith Porter for sharing the October 2023 version of his working paper, "Preliminary Benefit-Cost Analysis of Hail Seeding," and a follow-up Zoom meeting discussion that offered critical insights into this part of the study.

into the largest hailstone diameter (mm) by the factor of 0.81.

- Calculate $F_L = D_L/D'_L$, the ratio of the largest hailstone diameter of seeded versus unseeded storms. Applying Joe [2023] suggestion, the ratio is equal to the ratio of maximum VILs, $F_L = F_{max}$.

- Calculate the average hailstone diameters of seeded, D_A, and unseeded storms, D'_A, where hailstone diameters are calculated from the equation provided by Grieser and Hill [2019]: $D_A = (1.449)D_L^{0.649}$.

- Estimate the probability density function (PDF) parameters of the average hailstone diameter of seeded, D_A, and unseeded storms, D'_A, assuming they follow a gamma distribution (Grieser and Hill, 2019). Calculating F_α includes estimating the shape parameter of the fitted Gamma distribution over the PDF of average VILs (not log VIL). One can recover the shape factor by dividing the mean square of average VILs by the variance of that. If x has a Gamma distribution, the shape factor can be recovered from $\alpha = mean^2(x)/var(x)$.

- Define $F_\alpha = \alpha/\alpha'$ where F_α is the ratio of the estimated gamma distribution shape factor of seeded versus unseeded storms.

- Use the estimated effect of cloud seeding on hailstorm coverage area and define $F_C = A/A'$ where F_C is the ratio of hailstorm coverage of seeded versus the counterfactual unseeded storms. $F_C = 1$, since we estimated that seeding does not significantly impact the hail coverage area.

- Find the hailstorm occurrence frequency in Calgary and define $f'_h = f_h/F_C$, the unseeded hailstorm occurrence frequency. From Etkin [2018], the frequency of hailstorm occurrence in Calgary is $f'_h = f_h = 2.35$ storms per year.

- Estimate the change in the severity of hailstorms; that is, estimate changes in the hit rate (the number of hailstones per square meter per second) of seeded versus unseeded storms, $F_H = H_r/H'_r$. According to Grieser and Hill [2019], the hit rate as a function of a storm's largest hailstone, D_L, follows the equation $H_r = 11980 D_L^{1.237}$.

- Estimate the change in storms' duration (seconds) for seeded unseeded storms, $F_T = T/T'$. According to Grieser and Hill [2019], the duration as a function of a storm's largest hailstone, D_L, follows the equation $T = 5.92 D_L^{0.2652}$.

- Calculate the ratio of the number of hailstorms that strike a given area for seeded versus unseeded storms, $F_N = N/N' \approx F_H.F_T$ (Grieser and Hill, 2019).

- Calculate the average annual roof repair costs per unit hailstorm occurrence rate (marginal cost of repair) for seeded versus unseeded storms, $F_{MC} = AR/AR' \approx F_\alpha.F_N$. Based on Porter [2022] and Porter [2023], the equivalent average annual roof repair cost in Calgary per one hailstorm occurrence without seeding is $AR = 296$ Canadian dollars per square.

- Calculate the average annual reduction in roof repair cost in Calgary, $\Delta_1 = V.AR'.f'_h.(1-F_C.F_{MC})$, given the value for the equivalent number of single-family dwellings in Calgary, $V = 409,000$, from Porter [2022] and Porter [2023].

- Calculate the average annual reduction in auto losses, $\Delta_2 = \Delta_1.\beta$, where β is the ratio of average annual auto to property losses in the region. Based on Porter [2022] and Porter [2023], the ratio of average annual auto to property losses in the region from 2008 to 2020 is $\beta = 0.64$.

- Calculate the total annual loss reduction, $\Delta = \Delta_1 + \Delta_2$.

- Calculate the benefit-cost ratio, $BCR = \Delta/C$, where $C = 5$ million CAD, is the program's annual operational cost of cloud seeding from Tait [2022].

2.6.2 Results

Table 2.8 summarizes the estimated factors, outlined by Porter [2022] and Porter [2023], for the current and recommended seeding policies. The current seeding policy potentially increases the largest hailstone, the hit rate, and the duration of hailstorms. Consequently, the marginal repair cost remains nearly unchanged in comparison to the scenario of not seeding the storms, representing a mere 0.2% (i.e., (1-0.998) $\times$ 100) reduction.

In contrast, the recommended policy tends to reduce the largest hailstone, the hit rate, and the duration of hailstorms. This would result in a 5.1% (i.e., (1-0.949) $\times$ 100) decrease in the marginal repair cost compared to the scenario of not seeding the storms.

Table 2.8: Comparison of Outcomes - Current versus Recommended Seeding Policies

Variable	**Description of the Ratios**	**Current**	**Recommended**
F_L	Largest Hailstones	1.015	0.998
F_α	Shape factor of Gamma Dist.	0.976	0.951
F_C	Hailstorm Coverage Area	1.000	1.000
F_H	Hail Hit Rate	1.019	0.998
F_T	Hail Duration	1.004	1.000
F_{MC}	Marginal Cost of Repair	0.998	0.949

Table 2.9 illustrates how the policies' impact on the marginal cost of repair translates into the savings from roof and auto repair in Calgary, and the Benefit-cost of the hail suppression program. The current policy saves 1 million CAD annually on auto and roof repairs, but this amount does not cover the annual operational cost of 5 million CAD, resulting in a benefit-cost ratio of 0.2.

On the other hand, the recommended policy would save 23.4 million CAD annually on auto and roof repairs, which exceeds the operational cost, resulting in a benefit-cost ratio of 4.7.

Table 2.9: Saving in Damages (Annual - Millions CAD)

Category	**Current Policy**	**Recommended Policy**
Roof Repair Savings	0.6	14.3
Auto Repair Savings	0.4	9.1
Total Savings	1.0	23.4
Cost of Operation	5.0	5.0
Benefit-Cost Ratio	0.2	4.7

2.7 Conclusion

In this study, we measured the efficacy of cloud seeding in mitigating hail damage using radar data of 187 single storm tracks with over an hour life cycle within Alberta's Hail Alley from 2011 to 2020.

We utilized a dynamic panel data model complemented by System Generalized Method of Moments (GMM) estimators to estimate the effect of cloud seeding on the observed radar-measured Vertically Integrated Liquid (VIL) values of storms.

Our findings suggest that cloud seeding reduces VIL by 3% to 4% based on model specification. This observation supports the hypothesis that seeding could influence hailstone formation, potentially yielding smaller hailstones that might result in less severe damage.

The study highlights that the effectiveness of cloud seeding varies significantly with the storm's intensity and the developmental stages of the storms at the time the seeding effect appears. The largest impact of seeding, an 11% to 16% reduction in VIL, appears when the storm is far from its peak intensity. The effect of seeding alters as seeding continues in proximity to the storm's peak intensity, where seeding increases VIL by 6%.

These findings imply that the strategic timing and conditions under which seeding is implemented are crucial. The study recommends an adjustment to the current seeding policy, in which seeding activity should stop temporarily as the storms develop close to their maximum intensity and proceed with seeding afterward.

It is important to note that these results are subject to inherent limitations associated with the complexities of weather systems and the challenges in controlling for all influencing meteorological variables. While this research contributes to the body of knowledge on the impacts of cloud seeding on hail suppression, the results should be interpreted cautiously.

The economic analysis of this study indicates a favorable benefit-cost ratio from cloud seeding under the recommended seeding policy, suggesting that it could be a cost-effective method for reducing hail damage. Nonetheless, these economic assessments are based on model estimations and assumptions that require further validation through extended observational data and more comprehensive economic modeling.

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Chapter 3

3 The Effect of Public Climate Change Agreement on GHG Emissions

The Case of the US

3.1 Introduction

The United States (US) is a major source of greenhouse gas (GHG) emissions. For example, with less than 5 percent of the world's population, the US was responsible for 15 percent of fossil fuel and other CO2 emissions globally in 2014 (Boden et al., 2017). GHG emissions are linked to climate change, and scientists seem to have a broad consensus on the subject (Cook et al., 2013). However, public opinion in the US is far from reaching such a consensus.

According to Leiserowitz et al. [2023] , the percentage of Americans who agree that climate change is happening was 71 percent in 2009, decreased to 69 percent in 2016, then increased to 72 percent in 2021. So, approximately a third of the US population does not believe climate change is happening. Similarly, the percentage of Americans who agree that human activities, like GHG emissions, cause climate change was 57 percent in 2009, decreased to 52 percent in 2016, and went back to 57 percent in 2021. This means that approximately half of the US population does not think that emitting 15 percent of global CO2 emissions in one year, for example, is causing climate change. Further, and perhaps most importantly for policy support, between 40 percent and 50 percent of Americans do not think climate change will harm people in the present or the near future. This indicates a significant gap in the public agreement on climate change, its causes, and its effects. Therefore, in this paper, we aim to answer the following question: what is the quantitative effect of increasing public agreement on climate change (PCCA) in the US on GHG Emissions?

PCCA plays a vital role in shaping the socio-political context of climate change policymaking. For example, studies (e.g., Adger, 2003; Herrnstadt and Muehlegger, 2014) show that PCCA affects individual and collective climate change behavior. Examples include energy consumption, voting behavior, and collective actions to improve environmental standards. However, existing literature does not quantify the effect of PCCA on GHG emissions. This paper aims to fill this gap.

The pivotal role of PCCA in policymaking has motivated a growing body of research to highlight the mechanisms underlying the lack of public agreement on climate change observed in the US. Nisbet and Myers [2007], Boykoff and Boykoff [2007], Sampei and Aoyagi-Usui [2009], Schmidt et al. [2013], Brüggemann and Engesser [2017], and Shapiro [2016] are examples of studies that try to explain the causes and effects of climate change skepticism and denial in the US. These studies highlighted the roles of special interests, such as oil and gas companies and media coverage, in promoting climate change skepticism and denial.

The intricacy of the underlying mechanisms complicates the empirical approach to studying the relationship between PCCA and GHG emissions. For example, lobbying efforts of special interest groups try to influence policymakers directly to stop or slow the enacting of emission standards. These efforts include funding campaigns to promote climate change skepticism through media coverage. As a result, special interest groups may affect PCCA and GHG emission levels at the same time. In contrast, campaigns that support enacting emission standards may simultaneously increase PCCA and decrease GHG emission levels.

We propose an empirical model to estimate the impact of PCCA on GHG emissions in the US as follows. We use lagged temperature anomalies as instrumental variables (IV) to identify the impact of lagged PCCA on GHG emissions per capita in the following year. The IV identification strategy helps to infer that the association between variation in the PCCA and GHG emissions is a causal relationship.

We find that increasing PCCA is significantly related to decreasing GHG emissions per capita in the following year. The relationship between PCCA and the reduction in GHG emissions is evident: increasing PCCA by 10 percentage points is expected to reduce per capita GHG emissions by approximately 3 percentage points the following year. This relationship is robust across various specifications, including county-, time-, and state/time-fixed effects.

Further, we quantify the welfare impact of increasing PCCA in the US. For this purpose, we use the estimated effect of PCCA on GHG emissions that we estimate in this study, the estimated US population size in 2021 (approximately 330 million), and the estimated "social cost of carbon" ($6 for the US) as per Nordhaus [2017]. We find that increasing PCCA by 10pp is expected to decrease total GHG emissions per year by more than 5 million metric tons, resulting in an annual gross welfare gain of $32.4 billion. This can be viewed as a lower bound estimate since there are significantly higher estimates for the "social cost of carbon" (SCC). For example, Pindyck [2019] estimates SCC at $80, more than 13 times higher than the cost we used to quantify the welfare impact of increasing PCCA.

The rest of the paper is organized as follows: Section 2 presents data. Section 3 presents the estimation framework and benchmark results. Section 4 presents robustness checks. Section 5 presents an estimation of the welfare impact. Finally, a conclusion is provided in Section 6.

3.2 Data

3.2.1 PCCA

As a measure of PCCA in the US, we use the responses recorded in the ”Climate Change in the American Mind” surveys. These surveys ask samples of Americans about their agreement or disagreement on climate change. The surveys have data since 2008 at the state level and since 2014 at the county level. Example questions include whether climate change is happening and whether climate change is expected to harm people in the US in the present or near future (in 10 years). Table 1 shows the percentage of respondents answering yes to these questions in different years. This percentage is the PCCA measure we use to estimate the regression model parameters. The most recent survey was done in December 2022. It was a joint effort between the Yale Program on Climate Change Communication and the George Mason University Center for Climate Change Communication (Leiserowitz et al., 2023).

Table 3.1: PCCA in the US

	2009	2016	2021
Climate change is happening	71%	69%	72%
Climate change will harm people	-	49%	59%

3.2.2 Temperature Anomalies

Common factors can contribute to increased PCCA and decreased GHG emissions. For example, campaigns that raise awareness about the causes and effects of climate change can increase PCCA and, at the same time, push for regulations that can decrease GHG emissions. This poses an endogeneity problem as we want to quantify the effect of increasing PCCA on GHG emissions. For this reason, we use lagged temperature anomalies as instrumental variables for PCCA.

Data on temperature anomalies at the county level in the US is obtained from the Climate at a Glance System (CGS). The CGS has been developed to analyze monthly temperature and rainfall data across the US. Temperature anomaly is the difference between the 12-month average temperature and the average temperature in the previous century (i.e., 1901-2000). Temperature anomaly represents the difference between current and long-term average or expected temperatures. Table 2 shows the average temperature anomaly in Degrees Fahrenheit across US counties in different years.

Table 3.2: Average Temperature Anomaly in the US

	2009	2016	2021
Average Temperature Anomaly	0.13	2.89	2.20

A growing body of literature finds a strong relationship between temperature anomalies and public perception of climate change. For instance, Donner and McDaniels [2013] find a significant relationship between the previous 3-12 months' temperature anomalies and perceiving climate change. Another example is Hamilton and Stampone [2013], in which they find stronger effects of temperature anomalies that are closer in time.

Many studies try to explain the high correlation between temperature anomalies and the public perception of climate change. Myers et al. [2013] report that public perception of temperature anomalies can affect public beliefs regarding climate change. Whitmarsh [2009] relates this correlation to the non-expert's misunderstanding between the concepts of weather and climate. In other words, people tend to judge the validity of climate change based on temperature anomalies. Since lagged temperature anomalies can affect lagged PCCA but do not affect current GHG emissions, using lagged temperature anomalies as instrumental variables for PCCA is justified.

3.2.3 GHG Emissions

The US Environmental Protection Agency (EPA) has been tracking the GHG emissions of emitting facilities in the US through the Greenhouse Gas Reporting Program (GHGRP). In this paper, we use data on GHG emissions by direct emitters. These emitters must report total GHG emissions at their facility to EPA, and the data is available at the county level. We study the effect of PCCA on the GHG emissions of direct emitters registered in GHGRP. To construct a comparable measure of GHG emissions across counties, we use GHG emissions per capita. We sum the emissions of all direct emitters registered in each county; then, we divide total emissions by the county's population size to get GHG emissions per capita for each county. The measure is in terms of annual metric tons of CO2 equivalent per capita (tCO2 e. per capita) commonly used in literature.

3.2.4 Median Household Income

Usually, one of the main contributors to GHG emissions is the level of economic activity. In addition, the level of education and the type of employment in a given county may affect its GHG emissions per capita. For this reason, we use the median household income level in each county as a control variable in our regression models. Data on the county level is obtained from the US Census Bureau Poverty estimates.

3.3 Estimation Framework and Results

The primary goal of this paper is to quantify the impact of increasing PCCA on GHG emissions in the US. At the county level, there is tremendous heterogeneity in PCCA measures. For example, in 2021, the percentage of respondents who agreed that climate change is happening ranged from around 45 percent in Lawrence County, Kentucky, to around 87 percent in San Francisco County, California. In addition, there are significant within-county variations across time. For example, between 2014 and 2021, there was an 11-percentage point decrease in respondents who agree that climate change is happening in Jack County, Texas. In the same period, there was a 19-percentage point increase in respondents who agree that climate change is happening in Zapata County, Texas. Similarly, variations across counties and time in temperature anomalies were recorded over the same period. We use these variations to estimate the impact of PCCA on GHG emissions in the US.

Our panel data sample has 1,783 counties and four time periods. This makes the sample size 7,132 observations. Equation (3.1) presents the regression model in which the dependent variable is GHG emissions per capita in the current period, and the explanatory variable we are interested in is PCCA in the previous period. Data on emissions is available till 2021, while data on PCCA at the county level starts in 2014. For this reason, we use four time periods. We use data on emissions in 2015, 2017, 2019, and 2021, while we use data on PCCA in 2014, 2016, 2018, and 2020.

$$GHG_{it} = \gamma PCCA_{it-1} + \beta X_{it} + \alpha_i + \lambda_t + u_{it} \tag{3.1}$$

The dependent variable, GHG_{it}, is the log of total GHG emissions per capita (*tCO2 e. per capita*) at county i in period t. $PCCA_{it-1}$ is the public climate change agreement at county i in the previous period, $t-1$. As a measure of $PCCA$, we use the percentage of people who responded yes to the *"timing"* question in the *"Climate Change in the American Mind"* surveys. The *"timing"* question is whether climate change is expected to harm people in the US in the present or near future (in 10 years). It is reasonable to assume that the public's agreement on whether climate change will cause harm motivates action to decrease GHG emissions to slow climate change. As a robustness check, we repeat the estimation using another question, *"happening,"* as a measure of $PCCA$. The *"happening"* question is simply about whether climate change is happening.

We control for the median level of household income in each county in each period, X_{it}.

This is to account for differences in the levels of economic activity, education levels, and employment types across counties. We also include county fixed effects, α_i, to capture time-invariant characteristics of the counties that may be related to the emissions produced by the facilities they are hosting. Time-fixed effects are also included, λ_t. Finally, we have an error term, u_{it}.

To consistently estimate the impact of $PCCA$, we must ensure that $PCCA$ variations in the presented model are independent of the possible omitted variables and the unobservable factors. The independence assumption is strong since the chain of reactions, starting from changes in $PCCA$ and ending in GHG emissions, includes many factors that can influence both. For example, interest groups' lobbying efforts can directly influence policymakers toward decisions that keep GHG emissions at higher levels. In addition, these efforts can simultaneously promote skepticism of climate change among the public. As a result, we expect that $PCCA$ variation may not be orthogonal to the variation of the error term, u_{it}.

Therefore, we use lags of local temperature anomalies to instrument for $PCCA$ at the county level and alleviate the endogeneity arising from selection and omitted variables. Temperature anomaly is the difference between the 12-month average temperature and the average temperature in the previous century (i.e., 1901-2000). Previous studies have shown a correlation between temperature anomalies and $PCCA$. Since lagged temperature anomalies can affect lagged $PCCA$ but have no effect on current GHG emissions, we think using lagged temperature anomalies as instrumental variables for $PCCA$ is appropriate.

We use the two-stage least-square (2SLS) method to estimate the impact of lagged $PCCA$ on GHG emissions per capita in the following year. Equation (2) presents the first stage, where the endogenous variable, $PCCA$, is projected on temperature anomalies from previous periods ($Temp_{it-1}$, $Temp_{it-2}$, $Temp_{it-3}$) and other exogenous variables from equation (1). The "1" subscript in equation (2) denotes the first stage.

$$GHG_{it} = \gamma_2 P\hat{C}CA_{it-1} + \beta_2 X_{it} + \alpha_{2i} + \lambda_{2t} + u_{2it} \quad (3) \tag{3.2}$$

Table 3 shows the estimation results. The first stage relationship between temperature anomalies and PCCA is statistically significant: lags of temperature anomalies are significantly related to PCCA measures at the 99 percent confidence level. Further, PCCA is significantly related to GHG emissions per capita. A 1-percentage point increase in PCCA in one year is expected to cause a 0.279% decrease in GHG emissions per capita next year. This is the main result of this paper.

Next section, we perform robustness checks to confirm this result. In section 5, we calculate the welfare implication of increasing PCCA based on this estimation.

Table 3.3: Benchmark Estimation Results
Dependent Variable: Log(GHG emissions per capita)

Explanatory Variables	
Stage 1	
% Temp. Anomaly 1	0.133***
% Temp. Anomaly 2	-0.085***
% Temp. Anomaly 3	0.156***
Stage 2	
PCCA	**-0.279****
Log (Median Income)	1.351**
County Fixed Effects	Yes
Time Fixed Effects	Yes

* Significant at 90%, ** Significant at 95%, *** Significant at 99% confidence level.

3.4 Robustness

3.4.1 ”Timing” vs. ”Happening”

In the benchmark estimation, we used the answer to the question of *”timing”* as the measure of PCCA. We repeat the estimation using the percentage of people who responded yes to the *”happening”* question in the *”Climate Change in the American Mind”* surveys as a robustness check. As mentioned, the *”happening”* question is about whether climate change is happening.

Table 4 shows the estimation results. The first-stage relationship between temperature anomalies and PCCA remains statistically significant. Further, PCCA also remains significantly related to GHG emissions per capita. A 1-percentage point increase in PCCA in one year is expected to cause a 0.118% decrease in GHG emissions per capita next year.

The fact that the estimated coefficient is smaller when we use *”happening”* as a PCCA measure is not surprising. This is because simply agreeing that climate change is happening does not necessarily mean that the public also agrees that something needs to be done to decrease GHG emissions. It is possible that a group of people agree that climate change is happening, but they are not concerned about its effects. This is evident in the answers to the surveys. As shown in Table 1, the percentage of respondents who agree that climate change is happening is higher than that of respondents who agree that it will harm people in the present or near future.

** Significant at 90%, ** Significant at 95%, *** Significant at 99% confidence level.*

Table 3.4: Estimation Results Using "Happening" as a PCCA Measure
Dependent Variable: Log(GHG emissions per capita)

Explanatory Variables	
Stage 1	
% Temp. Anomaly 1	0.168***
% Temp. Anomaly 2	0.044**
% Temp. Anomaly 3	0.046*
Stage 2	
PCCA	**-0.118***
Log (Median Income)	0.521
County Fixed Effects	Yes
Time Fixed Effects	Yes

* Significant at 90%, ** Significant at 95%, *** Significant at 99% confidence level.

3.4.2 State-Time Effects

To control for time differentials in cross-state variations, we add a state×time variable to the model and repeat the estimation. This can capture heterogeneous institutional changes across states. The quantity and quality of environmental regulations adopted at the state level can affect producers' decisions and positively correlate with the state's average level of PCCA. These institutional innovations occur differently across the states. We aim to account for these types of institutional changes across time in different states in which counties are located.

Table 5 shows the estimation results. We use *"timing"* as the PCCA measure in this estimation since our comparison is with the benchmark results. As shown in Table 5, the results are almost identical to the benchmark estimation. A 1-percentage point increase in PCCA in one year is expected to cause a 0.280% decrease in GHG emissions per capita next year.

3.4.3 Current Temperature Anomaly

As an additional robustness check, we add the temperature anomaly in the current year as an explanatory variable in the model. Table 6 shows the estimation results. Again, we use *"timing"* as the PCCA measure in this estimation since our comparison is with the benchmark results. As shown in Table 6, the main conclusion holds, and the estimated coefficients are close in magnitude to the benchmark results. The first stage relationship between temperature anomalies and PCCA is statistically significant: lags of temperature anomalies are significantly related to PCCA measures at the 99 percent confidence level. Further, PCCA is significantly related to GHG emissions per capita. A 1-percentage point increase in PCCA in one year is expected to cause a 0.245% decrease in GHG emissions per capita next year.

Table 3.5: Estimation Results with State-Time Effects
Dependent Variable Log(GHG emissions per capita)

Explanatory Variables	
Stage 1	
% Temp. Anomaly 1	0.133***
% Temp. Anomaly 2	-0.086***
% Temp. Anomaly 3	0.157***
Stage 2	
PCCA	**-0.280****
Log (Median Income)	1.352**
County Fixed Effects	Yes
Time Fixed Effects	Yes
State*Time Effects	Yes

* Significant at 90%, ** Significant at 95%, *** Significant at 99% confidence level.

3.5 The Welfare Impact

In this section, we aim to analyze the economic significance of the existing PCCA gap in the US. Using the estimated coefficient, we perform a back-of-envelope calculation to evaluate the welfare impact of the PCCA gap. We use different estimates of the social cost of carbon (SCC) to monetize the adverse effects of climate change.

A large body of literature tries to monetize the consequences of climate change. Governmental bodies typically use the SCC estimates of an integrated assessment model (IAM) to assess the effects of environmental policy. IAMs estimate the reductions in GDP due to different climate change scenarios. These models simulate time paths for the atmospheric CO2 concentration and its impact on temperature. The temperature changes translate into GDP reductions. The Intergovernmental Panel on Climate Change (IPCC) uses Nordhaus [2017] estimates of SCC. Nordhaus [2017] updates the 2013 version of the Dynamic Integrated Model of Climate Change and Economy estimates that the global SCC in 2015 is 31.21($ /t CO2, 2010$). He estimates the regional SCC for the US to be 15.3% of the total damage, or 4.78 ($/t CO2, 2010$).

Pindyck [2019] presents a survey-based approach to estimating an average SCC. There is considerable uncertainty regarding the probability of alternative (or extreme) economic outcomes of climate change. Also, the required emissions reduction to prevent these events is uncertain. He relies on a survey of economists and climate science experts to produce the probabilities and the required emissions reduction. Based on the economists' responses, the average SCC is $80 per t CO2. When including non-economists, the average SCC is $200 per t CO2.

Using the benchmark estimated coefficient of PCCA, a percentage point increase in PCCA is expected to decrease GHG emissions per capita by $e^{-0.279} = 0.757$ t CO2. The estimated population size of the US in 2021 was 332 million. This means that a percentage point increase in PCCA is expected to decrease total GHG emissions in the US by about 251 million t CO2 annually (0.757 * 332 million). Using the estimates of SCC, this means that the estimated gross welfare benefits (as we are not estimating the potential cost of changing public perception) of increasing PCCA by one percentage point are between $1.2 billion and $50.2 billion annually.

Closing the PCCA gap means increasing the percentage of people who answer yes to the *"timing"* question, whether climate change will harm people in the present or near future, to 100%. In 2021, 59% responded yes to this question. This means that closing the PCCA gap requires a 41-percentage point increase. Using the estimates above, this means that closing the PCCA gap in the US can result in gross welfare benefits between $49 billion and $2 trillion annually. However, such an increase in PCCA is not marginal, so these estimates must be taken cautiously.

3.6 Conclusion

The US is a major contributor to global GHG emissions. While there seems to be a broad consensus among scientists about climate change and the link between GHG emissions and climate change, the US public lacks consensus on the subject. A significant percentage of the US public does not agree that climate change is happening or that it will harm people in the present or near future. This may be contributing to slowing down efforts to reduce GHG emissions in the US, which would worsen climate change.

In this paper, we estimate the impact of increasing the public agreement on climate change (PCCA) in one year on the US's GHG emissions per capita in the next year. We instrument for lagged PCCA using lagged temperature anomalies since these anomalies correlate to lagged PCCA but not current GHG emissions. We find that increasing public PCCA in the US is significantly related to lower GHG emissions.

Through the expected reductions in total GHG emissions, increasing PCCA can result in significant welfare g ains. Using our benchmark results and estimated ”social cost of carbon”, we find that increasing PCCA by a percentage point can result in \$1.2 billion to \$50.2 billion in annual gross welfare gains through reduced GHG emissions. Closing the PCCA gap can result in up to \$2 trillion in annual welfare gains through reduced GHG emissions.

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Appendices

A Examples of Abatement Technologies in Various Industries

A.1 Metals Manufacturing (e.g., Steel and Iron)

Business-as-Usual: Traditional blast furnaces with basic pollution controls.

Second-tier: Electric arc furnaces (less productive for certain products but with lower emissions).

Retrofit: Installation of advanced fabric filters or electrostatic precipitators on existing furnaces to reduce particulate emissions.

State-of-the-Art: Integrated steel mills with advanced energy recovery systems and pollution control technologies, enhancing both productivity and environmental performance.

A.2 Cement and Concrete Production

Business-as-Usual: Wet process kilns.

Second-tier: Vertical shaft kilns (less energy-efficient but potentially lower in certain pollutants).

Retrofit: Installing scrubbers or baghouse filters in existing kilns.

State-of-the-Art: Dry process kilns with preheaters and precalciners, improving energy efficiency and reducing emissions.

A.3 Chemical Manufacturing

Business-as-Usual: Traditional chemical reactors with minimal emission control.

Second-tier: Batch processing (may reduce productivity but can lower emissions for certain processes).

Retrofit: Upgrading existing reactors with improved sealing and venting systems.

State-of-the-Art: Continuous flow reactors using green chemistry principles, enhancing both efficiency and environmental performance.

A.4 Wood Products and Paper Manufacturing

Business-as-Usual: Conventional sawmills and pulp mills.

Second-tier: Mechanical pulping (less efficient than chemical pulping but with fewer chemical emissions).

Retrofit: Installing cyclones or baghouses in existing facilities to reduce wood dust and particulate emissions.

State-of-the-Art: Integrated pulp and paper mills with closed-loop water systems and advanced emission control technologies.

A.5 Mineral Processing

Business-as-Usual: Conventional crushing and grinding operations.

Second-tier: Manual sorting and processing (less efficient but may reduce dust generation).

Retrofit: Installing dust collection systems like fabric filters on existing equipment.

State-of-the-Art: Automated, high-efficiency processing plants with enclosed conveyor systems and advanced dust control.

A.6 Fossil Fuel Power Generation

Business-as-Usual: Coal-fired power plants with basic particulate controls.

Second-tier: Co-firing with biomass (reduces emissions but may affect energy output).

Retrofit: Upgrading existing plants with advanced scrubbers and particulate filters.

State-of-the-Art: Ultra-supercritical coal-fired power plants or natural gas combined cycle plants with integrated emissions control technologies offer higher efficiency and lower emissions.

A.7 Textile Manufacturing

Business-as-Usual: Traditional textile mills with minimal dust control.

Second-tier: Handloom weaving (less productive but with minimal dust generation).

Retrofit: Installing local exhaust ventilation systems in existing mills.

State-of-the-Art: Automated textile manufacturing with enclosed production areas and advanced air filtration systems.

B Decomposition of Manufacturing Emissions

I begin by defining the major components of manufacturing pollution emissions. The equation can be expressed as:

$$Z_t = \sum_s Z_{st} = \sum_s Q_{st}\bar{Z}_{st} = Q_t \sum_s \theta_{st}\bar{Z}_{st} \tag{3}$$

Where Z_t and Q_t are the aggregate manufacturing emissions and output, Z_{st}, Q_{st}, and $\bar{Z}_{st} = Z_{st}/Q_{st}$ are the sector emissions, output, and emission intensity. Finally, $\theta_{st} = Q_{st}/Q_t$ is the sector output share.

I can decompose the manufacturing emissions in the following identity statement:

$$\hat{Z} - 1 = (\hat{Z}_1 - 1) + (\hat{Z}_2 - \hat{Z}_1) + (\hat{Z} - \hat{Z}_2) \tag{4}$$

I assign the following relations to the variables $\hat{Z}$, $\hat{Z}_1$, and $\hat{Z}_2$ which are proportional changes in emissions levels Z, Z_1, and Z_2 with respect to the base year emissions, Z_0:

Base-line emissions: $$Z_0 = Q_0 \sum_s \theta_{s0}\bar{z}_{s0} \tag{5}$$

Emissions level: $$Z = Q_t \sum_s \theta_{st}\bar{z}_{st} \tag{6}$$

Counterfactual emissions 1: $$Z_1 = Q_t \sum_s \theta_{s0}\bar{z}_{s0} \tag{7}$$

Counterfactual emissions 2: $$Z_2 = Q_t \sum_s \theta_{st}\bar{z}_{s0} \tag{8}$$

I replace the above expressions and find the following statement:

$$\frac{Z_t}{Z_0} - 1 = \frac{Q_t \sum_s \theta_{s0}\bar{z}_{s0}}{Q_0 \sum_s \theta_{s0}\bar{z}_{s0}} - 1 + \frac{Q_t \sum_s \theta_{st}\bar{z}_{s0} - Q_t \sum_s \theta_{s0}\bar{z}_{s0}}{Z_0} + \frac{Q_t \sum_s \theta_{st}\bar{z}_{st} - Q_t \sum_s \theta_{st}\bar{z}_{s0}}{Z_0} \tag{9}$$

I simplify the above statement to derive the manufacturing emissions statistical decomposition equation:

$$\frac{\Delta Z_t}{Z_0} = \frac{\Delta Q_t}{Q_0} + \frac{Q_t \sum_s \Delta\theta_{st}\bar{z}_{s0}}{Z_0} + \frac{Q_t \sum_s \theta_{st}\Delta\bar{z}_{st}}{Z_0} \tag{10}$$

The identity statement (10) helps us to understand how changes in emissions can be broken down into three factors:

- Changes in emissions due to changes in the aggregate manufacturing output (Scale effect - 1st term)
- Changes in emissions due to changes in the sector output shares (Composition effect - 2nd term)
- Changes in emissions due to changes in sector emission intensities (Technique effect -3rd term)

When the value of manufacturing output, Q_t grows, manufacturing emissions, Z_t, increase even if the sector output shares, θ_{st}, and emission intensities, $\bar{Z}_{st}$ remain unchanged. This is known as *the scale effect*. On the other hand, *the composition effect* occurs when manufacturers switch to cleaner sectors, resulting in decreased emissions even if sector emission intensities stay the same. Finally, *the technique effect* occurs when manufacturers adopt cleaner processes or are replaced by new entrants with cleaner processes, resulting in declining sector emission intensities.

I use Air pollution emission levels by industry year from the National Pollution Report Inventory (NPRI), Manufacturing sales data from the Monthly survey of manufacturing (STATCAN –table 16100047), and Manufacturing price indices from the Industrial Product Price Index (STATCAN – table 18100032) to conduct the statistical decomposition.

I merge sector monthly sales and price indices to find sector monthly output value (Sales deflated by an industry price index). I aggregate the sectors' monthl output to calculate the annual sector output. I then generate sectors' annual sales from the monthly sales data. I calculate sectors' annual price indices using sectors' annual sales and output.

Figure 1.2 in the main text estimates the technique effect for six primary manufacturing air pollutants in Canada between 2004 and 2021.

Line 1 plots the total inflation-adjusted output for Canada's manufacturing sector, indexed so that 2004=100. As I showed, changes in output value can be seen as a scale effect. It illustrates the trend of pollution emissions if industries' composition and intensity had not changed. Line 2 depicts counterfactual pollution emissions, combining the effects of composition and scale on emissions (2004 = 100). Line 3 plots the trend in observed total manufacturing emissions (2004 = 100).

Note that the total emission reduction is the distance between line 1 and line 3. The technique effect is graphically represented by the distance between line 2 and line 3.

C The Model Solution

This section outlines steps leading to results, drawing parallels with standard heterogeneous firm models with monopolistic competition but with the addition of heterogeneous abatement technologies.

C.1 Consumers

Let Q_s represent the quantity of aggregate goods, which is a composite of the set of varieties consumed from sector s associated with the sector price index, which is

$$P_s = \left(\int_{\omega \in \Omega_s} p_s(\omega)^{1-\sigma_s} d\omega \right)^{\frac{1}{1-\sigma_s}}. \tag{11}$$

Then, the optimal consumption and expenditure decisions for each variety are as follows

$$q_s(\omega) = Q_s \left(\frac{p_s(\omega)}{P_s} \right)^{-\sigma_s}, \tag{12}$$

$$r_s(\omega) = E_s \left(\frac{p_s(\omega)}{P_s} \right)^{1-\sigma_s}, \tag{13}$$

where $E_s = P_s Q_s$ represents aggregate expenditure on the goods of sector s. Replacing Q_s in the consumption equation, demand is given by

$$q_s(\omega) = \frac{A_s}{p_s(\omega)^{\sigma_s}}, \tag{14}$$

where $A_s = E_s P_s^{\sigma_s - 1}$ is an index for the market size of sector s varieties.

C.2 Firms

Firms choose prices and abatement technologies to maximize profits in a monopolistic competition market. Since firms face a demand curve with constant elasticity σ_s, the first-order condition for price implies a constant mark-up, $\rho_s = \frac{\sigma_s}{\sigma_s - 1} > 1$, over marginal cost, $wt_{i,s}/\alpha_{i,s}\varphi$, such that

$$p_{i,s}(\varphi) = \frac{\rho_s w t_{i,s}}{\alpha_{i,s}\varphi}, \tag{15}$$

where $t_{i,s} = 1 + \tau_{i,s} e_{i,s}$ is the effective tax rate levy on each unit of production input. The market demand for a firm's good is determined by replacing the price equation in equation (38)

$$q_{i,s}(\varphi) = A_s \left(\frac{\alpha_{i,s}\varphi}{w\rho_s t_{i,s}} \right)^{\sigma_s}, \tag{16}$$

Rearranging the firm's production equation (6) from the main text and replacing the market demand equation (40), a firm requires $l_{i,s}(\varphi)$ units of production input to produce $q_{i,s}(\varphi)$

$$l_{i,s}(\varphi) = A_s \frac{(\alpha_{i,s}\varphi)^{\sigma_s - 1}}{(w\rho_s t_{i,s})^{\sigma_s}}. \tag{17}$$

The amount of pollution emission is endogenously determined using equation (41) and replacing input emission intensity (8) and output (40) from the main text:

$$z_{i,s} = A_s \frac{(\alpha_{i,s}\varphi)^{\sigma_s - 1}}{(w\rho_s t_{i,s})^{\sigma_s}} e_{i,s}. \tag{18}$$

The revenue of a firm is equal to $p_{i,s}(\varphi) q_{i,s}(\varphi)$. I replace the price equation (39), and the quantity equation (40) to find the following expression for revenue:

$$r_{i,s}(\varphi) = A_s \left(\frac{\alpha_{i,s}\varphi}{w\rho_s t_{i,s}} \right)^{\sigma_s - 1}. \tag{19}$$

A useful expression for profit is obtained by plugging the optimal prices (39), the expression for optimal demand (40), and pollution emission (42) into the profit function (5) in the main text

$$\pi_{i,s}(\varphi) = \frac{1}{\sigma_s} r_{i,s}(\varphi) - w f_{i,s}, \tag{20}$$

where $f_{i,s} = \left(\frac{\alpha_{i,s}}{e_{i,s}}\right)^{\sigma_s - 1} \bar{F}_s$ is the fixed cost of adopting technology i and has the functional form mentioned in equation (2); hence $\pi_{i,s}(\varphi)$ also depends on the market size index A_s.

$$\pi_{i,s}(\varphi) = \frac{A_s}{\sigma_s}\left(\frac{\alpha_{i,s}\varphi}{w\rho_s t_{i,s}}\right)^{\sigma_s - 1} - w f_{i,s},$$

Equation (20) defines profit as a linear function of productivity, $\varphi^{\sigma_s - 1}$. Finally, firms choose an abatement technology that maximizes profits:

$$i_s(\varphi) = \arg\max(\pi_{k,s}(\varphi)) \quad , k \in \{i\}_{i=0}^{K_s}$$

C.3 Deriving productivity cut-offs

Zero-profit productivity Cut-off

I begin with the derivation of zero-profit revenue. Let φ_s^* represent the productivity level at which a firm exhibits indifference towards participating in the competition, signifying zero profit, $\pi_s(\varphi_s^*) = 0$. It is assumed that regulators moderately increase the tax rate so that a group of firms always opt to maintain business as usual. Using equation (19), the zero-profit revenue is

$$r_s^* = r_{0,s}(\varphi_s^*) = A_s\left(\frac{\varphi_s^*}{w\rho_s t_{0,s}}\right)^{\sigma_s - 1}, \tag{21}$$

According to the profit equation (20), the equilibrium point of the zero-profit, denoted as the zero-profit cut-off, should meet the criteria of the subsequent equation.

$$r_s^* = \sigma_s w f_{0,s}, \tag{22}$$

Substituting in the revenue expression equation (20), solving for φ_s^*, and replacing for the functional form of the fixed cost equation (2) in the main text yields

$$\varphi_s^{*\sigma_s-1} = \frac{\sigma_s w^{\sigma_s} f_{0,s}}{A_s}(\rho_s t_{0,s})^{\sigma_s-1}. \tag{23}$$

Entrepreneurs with a productivity draw above the zero-profit cut-off decide to participate in the market. Equation (23) implies that more entrepreneurs stay out of the market due to more stringent regulations and adverse sector competition shock through A_s.

Other productivity cut-offs

In this model, there are two groups of productivity cut-offs. The first group includes productivity cut-offs that define the sector's technology composition. These are the point at which firms switch to a more expensive abatement. The second group includes a productivity cut-off that defines the technologies used in the equilibrium.

The first group: Suppose φ_1 denotes the productivity cut-off that firms are indifferent between exiting the market or employing technology 1. By definition, it is the productivity level at which $\pi_{1,s} = 0$. Using profit expression (20), solving for φ_1 gives an expression for the cut-off:

$$\varphi_{1,s}^{\sigma_s-1} = \frac{\sigma_s w^{\sigma_s} \rho_s^{\sigma_s-1} f_{1,s}}{A_s}. \tag{24}$$

Using profit expression (20), solving for $\varphi_{1,s}$ gives an expression for the cut-off:

$$\varphi_{1,s}^{\sigma_s-1} = \frac{\frac{f_{1,s}}{f_{0,s}}}{t_{0,s}^{\sigma_s-1}} \varphi_s^{*\sigma_s-1}. \tag{25}$$

It is worth mentioning that if the tax rate, $t_{0,s}^{\sigma_s-1}$, increases and surpasses $\frac{f_{1,s}}{f_{0,s}}$ in size, then $\varphi_s^* > \varphi_{1,s}$. This means that all surviving firms employ an abatement technology, and no firm will continue to do business as usual.

Now suppose $\varphi_{i,i+1,s}$ denote the productivity level such that a firm is indifferent about employing technology $i+1$ or keeps producing under technology $i > 0$. By definition, it is the productivity level at which $\pi_{i,s}(\varphi_{i,i+1,s}) = \pi_{i+1,s}(\varphi_{i,i+1,s})$. Using profit expression (20), solving for $\varphi_{i,i+1,s}$ gives an expression for the cut-off:

$$\varphi_{i,i+1,s}^{\sigma_s-1} = \frac{\sigma_s w^{\sigma_s} \rho_s^{\sigma_s-1}}{A_s} \frac{f_{i+1,s} - f_{i,s}}{\alpha_{i+1,s}^{\sigma_s-1} - \alpha_{i,s}^{\sigma_s-1}}. \tag{26}$$

Replacing for the zero-profit cut-off (23):

$$\varphi_{i,i+1,s}^{\sigma_s-1} = \frac{\frac{f_{i+1,s}-f_{i,s}}{f_{0,s}}}{t_{0,s}^{\sigma_s-1}(\alpha_{i+1,s}^{\sigma_s-1} - \alpha_{i,s}^{\sigma_s-1})} \varphi_s^{*\sigma_s-1}, \tag{27}$$

where $\frac{f_{i+1,s}-f_{i,s}}{f_{0,s}} > 0$ is the growth in the firm's fixed cost and $\alpha_{i+1,s}^{\sigma_s-1} - \alpha_{i,s}^{\sigma_s-1} > 0$ is the growth in the firm's revenue due to switching from technology i to $i+1$.

The second group: Suppose $\varphi_{0,i^*,s}$ denote the productivity level such that a firm is indifferent about employing technology i^* or keeps producing under business-as-usual technology under $t_{0,s}$. By definition, it is the productivity level at which $\pi_{0,s}(\varphi_{0,i^*,s}) = \pi_{i,s}(\varphi_{0,i^*,s})$. Using profit expression (20), solving for $\varphi_{0,i^*,s}$ for $i > 0$ gives an expression for the cut-off:

$$\varphi_{0,i^*,s}^{\sigma_s-1} = \frac{\sigma_s w^{\sigma_s} \rho_s^{\sigma_s-1}}{A_s} \frac{f_{i^*,s} - f_{0,s}}{\alpha_{i^*,s}^{\sigma_s-1} - \frac{1}{t_{0,s}^{\sigma_s-1}}}, \tag{28}$$

Replacing for the zero-profit cut-off (23):

$$\varphi_{0,i^*,s}^{\sigma_s-1} = \frac{\frac{f_{i^*,s}-f_{0,s}}{f_{0,s}}}{t_{0,s}^{\sigma_s-1}(\alpha_{i^*,s}^{\sigma_s-1} - 1)} \varphi_s^{*\sigma_s-1}. \tag{29}$$

In figure 1.6 from the main text, the productivity cutoff $\varphi_{0,i^*,s}$ corresponds to the intersection of the business-as-usual profit line (blue line) with the technology composition envelope (orange line). Firms with productivity levels lower than $\varphi_{0,i^*,s}$ choose business as usual technology over any inferior technologies to i^*. On the other hand, firms with productivity equal to or greater than $\varphi_{0,i^*,s}$ will prefer to choose i^* or superior technologies.

According to the equation 28, both i^* and $\varphi_{0,i^*,s}$ depend on the effective tax rate, $t_{0,s}$. As the tax rate increases $\varphi_{0,i^*,s}$ decreases, and more inferior abatement technologies are used.

C.4 Sector Average Productivity

In this segment, I follow the steps proposed by **?** to explain the unique equilibrium of the model. I initially illustrate that the zero-profit threshold constitutes sufficient statistics to determine the model's equilibrium and all sector-wide average variables.

Entrepreneurs draw their productivity measures from the Pareto distribution equation (1.4), which is characterized by the subsequent probability distribution function

$$g(\varphi) = \frac{\theta_s m_s^{\theta_s}}{\varphi^{\theta_s+1}}. \tag{30}$$

Suppose X_{in} represents the ex-ante probability of successful entry. Using the cumulative distribution of productivity, I can express X_{in} in terms of the zero-profit cut-off:

$$X_{\text{in,s}} = \Pr(\varphi > \varphi_s^*) = 1 - G(\varphi_s^*) = \left(\frac{m_s}{\varphi_s^*}\right)^{\theta_s}. \tag{31}$$

Alternatively, $X_{\text{in},s}$ represents the ratio of successful entrants

$$X_{\text{in,s}} = \frac{M_s}{M_s^e}. \tag{32}$$

I can define the average productivity level $\tilde{\varphi}$ as a function of the zero-profit cut-off, φ_s^*:

$$\tilde{\varphi}_s(\varphi_s^*)^{\sigma_s-1} = \frac{1}{X_{\text{in,s}}}\int_{\varphi_s^*}^{\infty} \varphi^{\sigma_s-1} g(\varphi) d\varphi. \tag{33}$$

Replacing for probability distribution function (52) and the ex-ante probability of successful entry (53):

$$\tilde{\varphi_s}^{\sigma_s-1} = \frac{\theta_s}{\theta_s - \sigma_s + 1}\varphi_s^{*\sigma_s-1}, \tag{34}$$

The expression $\theta_s - \sigma_s + 1 > 0$ indicates a particular constraint in the model, and I verify this condition by estimating the related parameters.

Equation (34) demonstrates that the sector's average productivity is an increasing function of the zero-profit threshold. This implies that implementing environmental policy and the occurrence of market shocks can potentially enhance the sector's average productivity by elevating the zero-profit cut-off.

C.5 The sector outcomes adjustment factor, average revenue, and average profits

The sector average revenue can be written regarding the sector average productivity and the zero-profit cut-off:

$$\tilde{r}_s = \frac{1}{X_{\text{in}}} \int_{\varphi^*_{0,s}}^{\infty} r_{i,s}(\varphi) g(\varphi) d\varphi. \tag{35}$$

First, I replace revenue (19), probability distribution function (30), and the ex-ante probability of successful entry (32) in the integral:

$$\tilde{r}_s = \left(\frac{\varphi^*_s}{m_s}\right)^{\theta_s} \int_{\varphi^*_s}^{\infty} A_s \left(\frac{\alpha_{i,s}\varphi}{w\rho_s t_{i,s}}\right)^{\sigma_s - 1} \frac{\theta_s m_s^{\theta_s}}{\varphi^{\theta_s+1}} d\varphi$$

$$\tilde{r}_s = \frac{\theta_s A_s}{(w\rho)^{\sigma_s-1}} \varphi_s^{*\theta_s} \int_{\varphi^*_s}^{\infty} \left(\frac{\alpha_{i,s}}{t_{i,s}}\right)^{\sigma_s-1} \frac{1}{\varphi^{\theta_s-\sigma_s+2}} d\varphi$$

$$\tilde{r}_s = \frac{\theta_s}{\theta_s - \sigma_s + 1} \cdot \frac{A_s}{(w\rho)^{\sigma_s-1}} \cdot \varphi_s^{*\theta_s} [\frac{1}{t_{0,s}^{\sigma_s-1}} \left(\frac{1}{\varphi_s^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{0,i^*,s}^{\theta_s-\sigma_s+1}}\right) + \alpha_{i^*,s}^{\sigma_s-1} \left(\frac{1}{\varphi_{0,i*,s}^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{i*,i*+1,s}^{\theta_s-\sigma_s+1}}\right)$$

$$+\alpha_{i*+1,s}^{\sigma_s-1} \left(\frac{1}{\varphi_{i*,i*+1,s}^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{i*+1,i*+2,s}^{\theta_s-\sigma_s+1}}\right) + \cdots + \alpha_{K-1,s}^{\sigma_s-1} \left(\frac{1}{\varphi_{K-2,K-1,s}^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{K-1,K,s}^{\theta_s-\sigma_s+1}}\right) + \frac{\alpha_{K,s}^{\sigma_s-1}}{\varphi_{K-1,K,s}^{\theta_s-\sigma_s+1}}]$$

$$\tilde{r}_s = \frac{\theta_s}{\theta_s - \sigma_s + 1} \cdot \frac{A_s}{(w\rho_s)^{\sigma_s-1}} \cdot \varphi_s^{*\theta_s} [\frac{1}{t_{0,s}^{\sigma_s-1}} \cdot \frac{1}{\varphi_s^{\theta_s-\sigma_s+1}} + \left(\alpha_{i^*,s}^{\sigma_s-1} - \frac{1}{t_{0,s}^{\sigma_s-1}}\right) \cdot \frac{1}{\varphi_{0,i^*,s}^{\theta_s-\sigma_s+1}}$$

$$+\left(\alpha_{i^*+1,s}^{\sigma_s-1}-\alpha_{i^*,s}^{\sigma_s-1}\right)\cdot\frac{1}{\varphi_{i^*,i^*+1,s}^{\theta_s-\sigma_s+1}}+\cdots+\left(\alpha_{K,s}^{\sigma_s-1}-\alpha_{K-1,s}^{\sigma_s-1}\right)\cdot\frac{1}{\varphi_{K-1,K,s}^{\theta_s-\sigma_s+1}}]$$

Second, I factor out $\frac{1}{t_{0,s}^{\sigma_s-1}}\cdot\frac{1}{\varphi_s^{\theta_s-\sigma_s+1}}$.

$$\tilde{r}_s=\frac{\theta_s}{\theta_s-\sigma_s+1}\cdot\frac{A_s}{(w\rho_s t_{0,s})^{\sigma_s-1}}\cdot\varphi_s^{*\sigma_s-1}[1+\left(t_{0,s}^{\sigma_s-1}\alpha_{i^*,s}^{\sigma_s-1}-1\right)\frac{\varphi_s^{\theta_s-\sigma_s+1}}{\varphi_{0,i^*,s}^{\theta_s-\sigma_s+1}}$$

$$+t_{0,s}^{\sigma_s-1}\left(\alpha_{i^*+1,s}^{\sigma_s-1}-\alpha_{i^*,s}^{\sigma_s-1}\right)\frac{\varphi_s^{\theta_s-\sigma_s+1}}{\varphi_{i^*,i^*+1,s}^{\theta_s-\sigma_s+1}}+\cdots+t_{0,s}^{\sigma_s-1}\left(\alpha_{K,s}^{\sigma_s-1}-\alpha_{K-1,s}^{\sigma_s-1}\right)\frac{\varphi_s^{\theta_s-\sigma_s+1}}{\varphi_{K-1,K,s}^{\theta_s-\sigma_s+1}}]$$

The preceding discussion necessitates some elaboration. Notably, the constituent terms in the above expression are contingent upon the tax rate. When the tax rate is sufficiently low, only a select group of highly productive firms may opt for the costliest state-of-the-art technology in the sub-list. Meanwhile, the remainder continue their business-as-usual strategies.

As the tax rate escalates, more abatement alternatives become available within the sector. In scenarios where the tax rate is exceptionally high, all abatement technologies within the sub-list, including those that may detrimentally affect the firm's productivity, appear as rational choices. This is particularly true for lower-productivity firms seeking to alleviate their tax burden.

Third, I solve the integral using expressions for productivity cut-offs (27):

$$\tilde{r}_s=\frac{\theta_s r_s^*}{\theta_s-\sigma_s+1}[1+\left(t_{0,s}^{\sigma_s-1}\alpha_{i^*,s}^{\sigma_s-1}-1\right)^{\frac{\theta_s}{\sigma_s-1}}\left(\frac{f_{0,s}}{f_{i^*,s}-f_{0,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}$$

$$+t_{0,s}^{\theta_s}\left(\alpha_{i^*+1,s}^{\sigma_s-1}-\alpha_{i^*,s}^{\sigma_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}}\left(\frac{f_{0,s}}{f_{i^*+1,s}-f_{i^*,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}+\cdots$$

$$+t_{0,s}^{\theta_s}\left(\alpha_{K,s}^{\sigma_s-1}-\alpha_{K-1,s}^{\sigma_s-1}\right)^{\frac{\theta_s}{\sigma_s-1}}\left(\frac{f_{0,s}}{f_{K,s}-f_{K-1,s}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}]$$

Fourth, replacing zero-profit revenue from equation (22), I derive an expression for the sector's average revenue:

$$\tilde{r}_s = \frac{\theta_s \sigma_s w f_{0,s} \gamma_{R,s}}{\theta_s - \sigma_s + 1} \tag{36}$$

where

$$\gamma_{R,s} = 1 + \left(t_{0,s}^{\sigma_s - 1} \alpha_{i^*,s}^{\sigma_s - 1} - 1\right)^{\frac{\theta_s}{\sigma_s - 1}} \left(\frac{f_{0,s}}{f_{i^*,s} - f_{0,s}}\right)^{\frac{\theta_s}{\sigma_s - 1} - 1}$$

$$+ t_{0,s}^{\theta_s} \left(\alpha_{i^*+1,s}^{\sigma_s - 1} - \alpha_{i^*,s}^{\sigma_s - 1}\right)^{\frac{\theta_s}{\sigma_s - 1}} \left(\frac{f_{0,s}}{f_{i^*+1,s} - f_{i^*,s}}\right)^{\frac{\theta_s}{\sigma_s - 1} - 1} + \cdots$$

$$+ t_{0,s}^{\theta_s} \left(\alpha_{K,s}^{\sigma_s - 1} - \alpha_{K-1,s}^{\sigma_s - 1}\right)^{\frac{\theta_s}{\sigma_s - 1}} \left(\frac{f_{0,s}}{f_{K,s} - f_{K-1,s}}\right)^{\frac{\theta_s}{\sigma_s - 1} - 1}$$

$\gamma_{R,s}$ is the sector outcomes adjustment factor (SOAF). It is a sufficient statistic that summarizes the effect of regulation and technological composition on the sector's average profit and revenue.

Each constituent term of $\gamma_{R,s}$ consists of positive numerical values, which makes $\gamma_{R,s}$ greater than one, $\gamma_{R,s} > 1$. Notably, if the environmental tax rate increases, $\gamma_{R,s}$ will also increase, but the exact degree of increase will depend on the abatement technologies used in the sector.

Furthermore, the size of $\gamma_{R,s}$ depends on the characteristics of the underlying abatement technologies. A lower difference between two consecutive technologies' abatement fixed costs and a larger difference between their productivity-enhancing measures are associated with larger $\gamma_{R,s}$.

I can derive the sector average profit by evaluating profit, equation (20), at the average productivity revenue from equation (36):

$$\bar{\pi}_s = \frac{\sigma_s - 1}{\theta_s - \sigma_s + 1} . w f_{0,s} \gamma_{R,s}. \tag{37}$$

As depicted by the equation (37), the expected profit is not a function of φ_s^*.

C.6 The free entry condition

I will use the ”free entry condition” to derive a new equation that relates average profits to average productivity. The ”free entry condition” suggests that in equilibrium, the cost associated with drawing productivity is equal to the expected profit, which can be expressed as follows:

$$M_s \bar{\pi}_s = M_s^e w f_s^e. \tag{38}$$

Since all firms operating within the market are making positive profits, entrepreneurs must expect positive profits from the productivity draws, too. This means that firms are expected to earn profits.

I substitute the ex-ante probability of market entry, as described in equations (31) and (32) into (38). Consequently, the average profit is expressed in terms of the entry sunk cost:

$$\bar{\pi}_s = w f_s^e \left(\frac{\varphi_s^*}{m_s}\right)^{\theta_s}. \tag{39}$$

Equation (39) characterizes the average profit as a strictly increasing function of the zero-profit cut-off.

C.7 The Uniqueness of Equilibrium

Equations (37) and (39) collectively determine a unique value for the equilibrium zero-profit entry cut-off:

$$\varphi_s^* = m_s \gamma_{R,s}^{1/\theta_s} \left[\left(\frac{f_{0,s}}{f_s^e}\right)\left(\frac{\sigma_s - 1}{\theta_s - \sigma_s + 1}\right)\right]^{1/\theta_s}$$

The above equation, mentioned in the main text as equation 1.19,

The free entry condition (38) can be written differently. The left-hand side is the sector profits gained by surviving firms. Using expressions for average revenue in (36) and average profit in equation (37), I can recover the free condition mentioned in equation (1.21) of the main text:

$$\frac{\sigma_s - 1}{\theta_s \sigma_s} R_s = w M_s^e f_s^e.$$

C.8 Factor Market-Clearing Condition

Since I am analyzing a closed economy, consumer expenditure on sector s goods should be equal to the sector's revenue; consequently, aggregate expenditure is equal to aggregate revenue:

$$E_s = R_s, \quad E = R$$

Also, to preserve the factor market clearing condition, sector aggregate expenditure on factor input must match the sector aggregate revenue as follows:

$$w L_s = R_s$$

I confirm this condition by directly summing up firms' factor allocation for each activity. The aggregate factor required for production and tax is the sum of firms' factor demand and tax payment:

$$L_s^p + L_s^\tau = \frac{M_s}{X_{in}} \int_{\varphi_s^*}^{\infty} (l_{i,s}^p + \tau_{i,s} z_{i,s}(\varphi)) g(\varphi) d\varphi$$

Using the expressions for firm labor input (17) and emissions (18), the probability of successful entry (31), Pareto probability distribution (30), productivity cut-offs (23, 27, and 29), solving for the integral, and replacing for the zero-profit revenue (22), the aggregate factor required for production and tax payment is given by:

$$L_s^p + L_s^\tau = M_s \theta_s \left(\frac{\sigma_s - 1}{\theta_s - \sigma_s + 1} \right) f_{0,s} \gamma_{R,s} = \theta_s M_s^e f_s^e$$

The aggregate factor used to adopt abatement technologies is as follows:

$$L_s^f = \frac{M_s}{X_{in}} \int_{\varphi_s^*}^{\infty} f_{i,s} g(\varphi) d\varphi$$

Using the expressions for the probability of successful entry (31), Pareto probability distribution (30), productivity cut-offs (23, 27, and 29), solving for the integral, and replacing for the zero-profit revenue (22), the aggregate factor required to adopt abatement technologies is given by:

$$L_s^f = M_s f_{0,s} \gamma_{R,s} = (\frac{\theta_s}{\sigma_s - 1} - 1) M_s^e f_s^e$$

At the sector level, the aggregate labor sunk to draw productivity is given by:

$$L_s^e = M_s^e f_s^e$$

Market clearing condition (9) holds in the equilibrium. Firms allocate their input to sink the entry cost, $l_{i,s}^e$, produce goods, $l_{i,s}^p$, invest in abatement technology, $l_{i,s}^f$, and pay for the environmental taxes, $l_{i,s}^\tau$. Summing all labor allocations, the aggregate factor demand is as follows:

$$L_s = L_s^e + L_s^p + L_s^\tau + L_s^f = \frac{\sigma_s \theta_s}{\sigma_s - 1} M_s^e f_s^e \quad .$$

C.9 Average pollution emission and emission efficiency factor

The level of pollution emission within a particular sector is determined by aggregating pollution emissions from the individual firms in that sector:

$$\tilde{z}_s = \frac{1}{X_{\text{in}}} \int_{\varphi_s^*}^{\infty} z_{i,s}(\varphi) g(\varphi) d\varphi$$

Replacing for firm's pollution (18) and using probability distribution function (30), and the ex-ante probability of successful entry (32):

$$\tilde{z}_s = \left(\frac{\varphi_s^*}{m_s}\right)^{\theta_s} \int_{\varphi_s^*}^{\infty} \frac{A_s e_{i,s}(\alpha_{i,s}\varphi)^{\sigma_s-1}}{(w\rho_s t_{i,s})^{\sigma_s}} \frac{\theta_s m_s^{\theta_s}}{\varphi^{\theta_s+1}} d\varphi$$

$$\tilde{z}_s = \frac{\theta_s A_s}{w\rho^{\sigma_s}} \varphi_s^{*\theta_s} \int_{\varphi_s^*}^{\infty} \frac{e_{i,s}\alpha_{i,s}^{\sigma_s-1}}{t_{i,s}^{\sigma_s}} \frac{1}{\varphi^{\theta_s-\sigma_s+2}} d\varphi$$

$$\tilde{z}_s = \frac{\theta_s}{\theta_s-\sigma_s+1} \frac{A_s}{(w\rho)^{\sigma_s}} \varphi_s^{*\theta_s} [\left(\frac{e_{0,s}}{t_{0,s}{}^{\sigma_s}}\right)\left(\frac{1}{\varphi_s{}^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{i^*,s}{}^{\theta_s-\sigma_s+1}}\right)$$

$$+ e_{i^*,s}\alpha_{i^*,s}{}^{\sigma_s-1}\left(\frac{1}{\varphi_{i^*,s}{}^{\theta_s-\sigma_s+1}} - \frac{1}{\varphi_{i^*,i^*+1,s}{}^{\theta_s-\sigma_s+1}}\right) + \cdots + \frac{e_{K,s}\alpha_{K,s}{}^{\sigma_s-1}}{\varphi_{K-1,K,s}{}^{\theta_s-\sigma_s+1}}]$$

$$\tilde{z}_s = \frac{\theta_s}{\theta_s-\sigma_s+1} \frac{A_s}{(w\rho)^{\sigma_s}} \varphi_s^{*\theta_s} [\left(\frac{e_{0,s}}{t_{0,s}{}^{\sigma_s}}\right) \frac{1}{\varphi_s{}^{\theta_s-\sigma_s+1}} + \left(e_{i,s} - \frac{e_{0,s}}{t_{0,s}{}^{\sigma_s}}\right) \frac{1}{\varphi_{0,i,s}{}^{\theta_s-\sigma_s+1}}$$

$$+ \left(e_{i^*+1,s}\alpha_{i^*+1,s}{}^{\sigma_s-1} - e_{i^*,s}\alpha_{i^*,s}{}^{\sigma_s-1}\right) \frac{1}{\varphi_{i^*,i^*+1,s}{}^{\theta_s-\sigma_s+1}} + \cdots + \left(e_{K,s}\alpha_{K,s}{}^{\sigma_s-1} - e_{K-1,s}\alpha_{K-1,s}{}^{\sigma_s-1}\right) \frac{1}{\varphi_{K-1,K,s}{}^{\theta_s-\sigma_s+1}}]$$

Factorizing out $\left(\frac{e_{0,s}}{t_{0,s}{}^{\sigma_s}}\right) \frac{1}{\varphi_s{}^{\theta_s-\sigma_s+1}}$:

$$\begin{aligned}
\tilde{z}_s = \frac{\theta_s}{\theta_s-\sigma_s+1} \frac{A_s}{(w\rho)^{\sigma_s}} \frac{e_{0,s}}{t_{0,s}{}^{\sigma_s}} \varphi_s^{*\sigma_s-1} \Bigg[1 &+ \left(\frac{e_{i^*,s} t_{0,s}{}^{\sigma_s}}{e_{0,s}} - 1\right) \frac{\varphi_s{}^{\theta_s-\sigma_s+1}}{\varphi_{i^*,s}{}^{\theta_s-\sigma_s+1}} \\
&+ \frac{t_{0,s}{}^{\sigma_s}}{e_{0,s}} \left(e_{i^*+1,s}\alpha_{i^*+1,s}{}^{\sigma_s-1} - e_{i^*,s}\alpha_{i^*,s}{}^{\sigma_s-1}\right) \frac{\varphi_s{}^{\theta_s-\sigma_s+1}}{\varphi_{i^*,i^*+1,s}{}^{\theta_s-\sigma_s+1}} + \ldots \\
&+ \frac{t_{0,s}{}^{\sigma_s}}{e_{0,s}} \left(e_{K,s}\alpha_{K,s}{}^{\sigma_s-1} - e_{K-1,s}\alpha_{K-1,s}{}^{\sigma_s-1}\right) \frac{\varphi_s{}^{\theta_s-\sigma_s+1}}{\varphi_{K-1,K,s}{}^{\theta_s-\sigma_s+1}} \Bigg]
\end{aligned}$$

Replacing for the zero-profit revenue (22) and productivity cut-offs (27)

$$
\begin{aligned}
\tilde{z}_s = \frac{\theta_s}{\theta_s-\sigma_s+1}\frac{w\sigma_s f_{0,s}e_{0,s}}{w\rho_s t_{0,s}}\Bigg[1 &+ \left(\frac{e_{i^*,s}t_{0,s}^{\sigma_s}}{e_{0,s}}-1\right)\left(\frac{t_{0,s}^{\sigma_s-1}-1}{\frac{f_{i^*,s}-f_{0,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\\
&+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{i^*+1,s}\alpha_{i^*+1,s}^{\sigma_s-1}-e_{i^*,s}\alpha_{i,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{i^*+1,s}^{\sigma_s-1}-\alpha_{i^*,s}^{\sigma_s-1}}{\frac{f_{i^*+1,s}-f_{i^*,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\\
&+\dots\\
&+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{K,s}\alpha_{K,s}^{\sigma_s-1}-e_{K-1,s}\alpha_{K-1,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{K,s}^{\sigma_s-1}-\alpha_{K-1,s}^{\sigma_s-1}}{\frac{f_{K,s}-f_{K-1,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\Bigg]
\end{aligned}
$$

Thus, sector average pollution emission is as follows:

$$
\tilde{z}_s = \frac{\theta_s(\sigma_s-1)}{\theta_s-\sigma_s+1}\frac{f_{0,s}e_{0,s}}{t_{0,s}}\gamma_{Z,s} \tag{40}
$$

where

$$
\begin{aligned}
\gamma_{Z,s} = 1 &+ \left(\frac{e_{i^*,s}t_{0,s}^{\sigma_s}}{e_{0,s}}-1\right)\left(\frac{t_{0,s}^{\sigma_s-1}-1}{\frac{f_{i^*,s}-f_{0,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\\
&+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{i^*+1,s}\alpha_{i^*+1,s}^{\sigma_s-1}-e_{i^*,s}\alpha_{i^*,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{i^*+1,s}^{\sigma_s-1}-\alpha_{i^*,s}^{\sigma_s-1}}{\frac{f_{i^*+1,s}-f_{i^*,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}\\
&+\dots\\
&+ \frac{t_{0,s}^{\theta_s+1}}{e_{0,s}}\left(e_{K,s}\alpha_{K,s}^{\sigma_s-1}-e_{K-1,s}\alpha_{K-1,s}^{\sigma_s-1}\right)\left(\frac{\alpha_{K,s}^{\sigma_s-1}-\alpha_{K-1,s}^{\sigma_s-1}}{\frac{f_{K,s}-f_{K-1,s}}{f_{0,s}}}\right)^{\frac{\theta_s}{\sigma_s-1}-1}
\end{aligned}
$$

is the sector emissions adjustment factor (SEAF) that represents the effect of sector technological composition on sector average emissions when firms face an environmental tax. I can write sector emissions in terms of sector revenue, dividing the above equation by sector average revenue in equation (36):

$$
\frac{Z_s}{R_s} = \frac{e_{0,s}}{w\rho}\frac{1}{T_s} \tag{41}
$$

where

$$T_s = t_{0,s}\frac{\gamma_{R,s}}{\gamma_{Z,s}} \tag{42}$$

is the stringency of environmental regulation, including environmental tax and the overall effect of the sector's technological composition on sector emissions, $\gamma_{R,s}/\gamma_{Z,s}$. The last step is to use the equation (1.21) to replace for sector revenue in the above equation and derive the equation (1.24) in the main text:

$$Z_s = \frac{\theta_s e_{0,s}}{T_s} M_s^e f_s^e$$

C.10 Sector Sales Price

I start with the definition in equation (11). In this model, the sector sales price is the sum of the inverse of firms' sales prices (not the average price). Thus, I can write the following definition for sector (sales) price:

$$P_s = \left(\frac{M_s}{X_{in}}\int_{\varphi_s^*}^{\infty} p_s(\varphi)^{1-\sigma_s} g(\varphi)d\varphi\right)^{\frac{1}{1-\sigma_s}}. \tag{43}$$

From firm revenue and price equations (19) and (15), the firm price can be written as $p_s(\varphi)^{1-\sigma_s} = r_s(\varphi)/A_s$. Replacing this expression in the above equation, it follows that:

$$P_s = \left(\frac{M_s}{A_s X_{in}}\int_{\varphi_s^*}^{\infty} r_s(\varphi)g(\varphi)d\varphi\right)^{\frac{1}{1-\sigma_s}},$$

which I solved the same integral for average sector revenue. Using the solution for average sector revenue, I can write the following:

$$P_s = \left(\frac{\theta_s}{\theta_s - \sigma_s + 1}\cdot\frac{\varphi_s^{*\sigma_s - 1}}{(w\rho_s t_{0,s})^{\sigma_s - 1}} M_s \gamma_{R,s}\right)^{\frac{1}{1-\sigma_s}}$$

I can rewrite the above equation to derive the equation (1.22) in the main text:

$$P_s = \left(\frac{\theta_s - \sigma_s + 1}{\theta_s}\right)^{\frac{1}{\sigma_s - 1}} w\rho \left(\frac{t_{0,s}}{\varphi_s^*}\right)\left(\frac{1}{M_s^e}\right)^{\frac{1}{\sigma_s - 1}}$$

C.11 Sector Output

Since sector output is $Q_s = R_s/P_s$, I can derive the sector output equation in the main text (1.23) using sector revenue (1.21) and price (1.22) equations:

$$Q_s = \theta_s \left(\frac{\theta_s}{\theta_s - \sigma_s + 1}\right)^{\frac{1}{\sigma_s - 1}} f_s^e \frac{\varphi_s^*}{t_{0,s}} (\hat{M}_s^e)^{\frac{\sigma_s}{\sigma_s - 1}}$$

In terms of proportional changes, we have:

$$\hat{Q}_s = (\hat{M}_s^e)^{\frac{\sigma_s}{\sigma_s - 1}} \frac{\hat{m}_s \hat{\gamma}_{R,s}^{\frac{1}{\theta_s}}}{\hat{t}_{0,s}}$$

D Proofs of Propositions 1 to 4

D.1 Proof of Proposition 1

Suppose that for two distinct technologies m and l in the original list, $f_m = f_l = f$. The technology with a higher productivity booster measure strictly dominates the other one. Suppose $\alpha_m > \alpha_l$; I demonstrate that $\pi_m(\varphi) > \pi_l(\varphi)$ regardless of productivity and that the following statement is true:

$$\left(\frac{A}{\sigma}\right)\left(\frac{\alpha_m\varphi}{w\rho}\right)^{\sigma-1} - wf > \left(\frac{A}{\sigma}\right)\left(\frac{\alpha_l\varphi}{w\rho}\right)^{\sigma-1} - wf$$

Eliminating fixed costs and other factors from both sides yields the following true statement: $\alpha_l^{\sigma-1} > \alpha_k^{\sigma-1}$. That is, the profit gained by a firm utilizing m is strictly greater than the profit it gains utilizing l, independent of its productivity.

If I assume the opposite, then k is dominated by i. Thus, for two distinct technologies m and l, in the sub-list $f_m \neq f_l$. ■

D.2 Proof of Proposition 2

Assume that $f_m < f_l$ but $\alpha_m \geq \alpha_l$. Then, the profit gained by a firm employing technology m, denoted by π_m, surpasses the profit gained when employing technology l, denoted by π_l, independent of the firm's productivity. In essence, technology m strictly dominates technology l, creating a scenario where firms will refrain from adopting technology l given the availability of technology m. Consequently, technology l can be excluded from the list. In mathematical terms, I prove:

$$f_m < f_l \text{ but } \alpha_m \geq \alpha_l \rightarrow \pi_m(\varphi) > \pi_l(\varphi) \quad \forall\varphi > 0$$

That is to show the following statement is true:

$$\left(\frac{A}{\sigma}\right)\left(\frac{\alpha_m\varphi}{w\rho}\right)^{\sigma-1} - wf_m > \left(\frac{A}{\sigma}\right)\left(\frac{\alpha_l\varphi}{\rho}\right)^{\sigma-1} - wf_l$$

Rearranging the above statement, I have

$$wf_l - wf_m > \left(\frac{A}{\sigma}\right)\left(\frac{\varphi}{w\rho}\right)^{\sigma-1}(\alpha_l^{\sigma-1} - \alpha_m^{\sigma-1})$$

Since the left-hand side of the inequality is a positive number and the right-hand side is a non-positive number, the inequality holds, and the statement is true. That is, technology m strictly dominates technology l. Thus, l can be eliminated; hence, it is not part of the sub-list.

I conclude that for the surviving technologies from the process of eliminating strictly dominated strategies, it is always the case that, for any two distinct technologies, m and l, $f_m < f_l \rightarrow \alpha_m < \alpha_l$. The costlier the abatement is, the more productive it is. ■

D.3 Proof of Proposition 3

I show the possible orders for these three cut-offs and conclude that only the above orders can hold. Without loss of generality and for simplicity, suppose that I select three back-to-back technologies 2,3, and 4. I want to show that only the following orders can be held: $\varphi_{2,3} \leq \varphi_{2,4} \leq \varphi_{3,4}$.

I begin with eliminating the case where $\varphi_{2,3} = \varphi_{2,4} = \varphi_{3,4} = \varphi^*$. Firms with productivity lower than φ^* will choose 2 since $2 \succ 3$ and $2 \succ 4$. Firms above φ^* choose 4, since $4 \succ 3$, $3 \succ 2$, and $2 \succ 4$. Thus, technology 3 is strictly dominated by 2 and 4.

There are six possible ways to dominate these cut-offs. I analyze them one by one:

a. $\varphi_{3,4} \leq \varphi_{2,3} \leq \varphi_{2,4}$ (Contradicting preferences in region III)

In Region III, firms have the following preferences: $(2 \succ 1)$ & $(4 \succ 3)$ & $(3 \succ 2)$ & $(2 \succ 4)$. By transitivity, I reach the following contradictory preferences: $(2 \succ 1)$ & $(3 \succ 2)$ & $(2 \succ 3)$. This contradiction persists in the case of $\varphi_{2,3} = \varphi_{3,4}$. In the case of $\varphi_{2,3} = \varphi_{2,4}$, in regions I, II, and III, firms choose 2, and in region IV, firms choose 4. Thus, technology 3 is strictly dominated by 2 and 4.

b. $\varphi_{3,4} \leq \varphi_{2,4} \leq \varphi_{2,3}$ (Other ones strictly dominate technology 3)

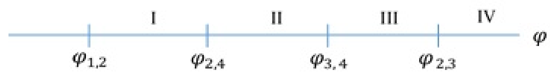
In Region I, firms choose 2. In Region II, firms choose 2 since they have the following preferences: $(2 \succ 1)$ & $(4 \succ 3)$ & $(2 \succ 4)$ & $(2 \succ 3)$. In Region III, firms choose 4 since they have the following preferences: $(2 \succ 1)$ & $(4 \succ 3)$ & $(4 \succ 2)$ & $(2 \succ 3)$. In Region IV, firms choose 4 since they have these preferences: $(2 \succ 1)$ & $(4 \succ 3)$ & $(4 \succ 2)$ & $(3 \succ 2)$. Thus, firms overlook 3, strictly dominated by 2 and 4; hence, 3 is not on the shortlist. This result persists in the cases of $\varphi_{2,3} = \varphi_{2,4}$ and $\varphi_{2,4} = \varphi_{3,4}$.

c. $\varphi_{2,3} \leq \varphi_{3,4} < \varphi_{2,4}$ (Contradicting preferences in region II)

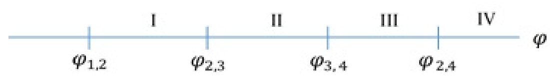
In Region II, there is an issue of contradictory preferences since $(2 \succ 1)$ & $(4 \succ 2)$ & $(2 \succ 3)$ & $(3 \succ 4)$, and by transitivity, $(4 \succ 2)$ & $(2 \succ 4)$. This result persists if $\varphi_{2,3} = \varphi_{3,4}$. Again, if $\varphi_{2,3} = \varphi_{2,4}$, then 3 is strictly dominated by 2 and 4.

d. $\varphi_{2,3} \leq \varphi_{2,4} \leq \varphi_{3,4}$ (Contradicting preferences in region II)

Region III has a contradiction $(4 > 2)$ & $(2 > 4)$. This contradiction persists in the case of $\varphi_{2,3} = \varphi_{3,4}$. e. $\varphi_{2,3} \leq \varphi_{3,4} < \varphi_{2,4}$ (Contradicting preferences in region III)



In Region III, there is a contradiction between $(4 > 2)$ & $(2 > 4)$. This contradiction persists in the case of $\varphi_{2,3} = \varphi_{3,4}$. f. $\varphi_{2,3} \leq \varphi_{2,4} \leq \varphi_{3,4}$



In Region I, firms choose 2; in Region II, firms choose 3; in Region III, firms choose 4. I do not encounter contradicting preferences or strictly dominated technologies. Thus, by induction, this ordering is the only acceptable ordering of technology cut-offs.

As a result of Proposition 3, I derive a condition to sort the technologies, thereby effectively assembling the list. Considering three technologies from the list, l, $l+1$, and $l+2$, where $f_l < f_{l+1} < f_{l+2}$. Based on Proposition 3, the subsequent productivity cut-offs must meet the following conditions:

$$\varphi_{l,l+1} < \varphi_{l,l+2}$$

By definition, at the cut-offs, a firm is indifferent between using technologies; that is, for l and $l+1$:

$$\pi_l(\varphi_{l,l+1}) = \pi_{l+1}(\varphi_{l,l+1})$$

This can be written as:

$$\frac{A}{\sigma}\left(\frac{\alpha_l \varphi_{l,l+1}}{w\rho}\right)^{\sigma-1} - wf_l = \frac{A}{\sigma}\left(\frac{\alpha_{l+1}\varphi_{l,l+1}}{w\rho}\right)^{\sigma-1} - wf_{l+1}$$

Replacing for fixed costs and rearranging:

$$wf_{l+1} - wf_l = \frac{A}{\sigma}\left(\frac{\varphi_{l,l+1}}{w\rho}\right)^{\sigma-1}\left(\alpha_{l+1}^{\sigma-1} - \alpha_l^{\sigma-1}\right)$$

From this, the expression for the cut-off is derived as:

$$\varphi_{l,l+1}^{\sigma-1} = \frac{\sigma\rho^{\sigma-1}}{w^{\sigma}A}\left(\frac{f_{l+1} - f_l}{\alpha_{l+1}^{\sigma-1} - \alpha_l^{\sigma-1}}\right)$$

Similarly, $\varphi_{i,i+2}$ and $\varphi_{i+1,i+2}$ are illustrated as:

$$\varphi_{l,l+2}^{\sigma-1} = \frac{\sigma\rho^{\sigma-1}}{w^{\sigma}A}\left(\frac{f_{l+2} - f_l}{\alpha_{l+2}^{\sigma-1} - \alpha_l^{\sigma-1}}\right)$$

and

$$\varphi_{l+1,l+2}^{\sigma-1} = \frac{\sigma\rho^{\sigma-1}}{w^{\sigma}A}\left(\frac{f_{l+2} - f_{l+1}}{\alpha_{l+2}^{\sigma-1} - \alpha_{l+1}^{\sigma-1}}\right)$$

Proposition 3 dictates that a specific condition must be met. If this condition is not fulfilled, the strategy denoted as $l+1$ is strictly dominated and needs elimination from the list.

$$\frac{f_{l+1} - f_l}{\alpha_{l+1}^{\sigma-1} - \alpha_l^{\sigma-1}} \leq \frac{f_{l+2} - f_l}{\alpha_{l+2}^{\sigma-1} - \alpha_l^{\sigma-1}} \leq \frac{f_{l+2} - f_{l+1}}{\alpha_{l+2}^{\sigma-1} - \alpha_{l+1}^{\sigma-1}}.\blacksquare$$

D.4 Proof of Proposition 4

The pollution intensity from the model is defined as $\bar{z}_i(\varphi) = e_i/\alpha_i\varphi$. Upon applying the functional form of the fixed cost associated with technology adoption, I can transform the equation for pollution intensity, using the functional form of the fixed cost of adoption in equation (1.3), yielding:

$$\bar{z}_i(\varphi) = \frac{1}{\varphi F^{-1}(f_i)}$$

where F^{-1} is the inverse function of F, which is increasing in f_i. From Proposition 3, I understand that the fixed cost of adoption, f_i, is a non-decreasing function of productivity φ. Given that $\bar{F}$ is a positive constant, it follows that the pollution intensity, $\bar{z}_i(\varphi)$, is a decreasing function of productivity φ. ■

E Estimating the Pareto Distribution Shape factor θ and Elasticity of Substitution σ

The investigation commences with an estimation of the shape parameter of the revenue distribution of firms. Under the premise that the distribution of firms' productivity adheres to the Pareto principle with a shape parameter defined as θ_s, one can infer from Equation 13 that the distribution of the respective revenues r_s is also Pareto, with the shape parameter recalibrated to $\frac{\theta_s}{\sigma_s - 1}$. It is essential to note that the upper tail of the Pareto cumulative distribution function is utilized to calculate revenues.[1]

$$\Pr\{r_{i,s} > r_{m,s}\} = \left(\frac{r_{m,s}}{r_{i,s}}\right)^{\frac{\theta_s}{\sigma_s - 1}} e^{i_{i,s}} \quad \text{for} \quad X_{i,s} \geq m_{i,s} \tag{44}$$

where $i_{i,s}$ represents exogenous idiosyncratic shocks to firms' revenues. The left-hand side is the revenue rank of the firm. Taking logs gives us the following expression:

$$\ln\left(\Pr\{r_{i,s} > r_{m,s}\}\right) = \alpha_{0,s} + \alpha_{1,s}\ln(r_{i,s}) + \epsilon_{i,s} \tag{45}$$

Equation (86) can be estimated separately for each sector. The Pareto shape parameter is then given by $\frac{\theta_s}{\sigma_s - 1} = -\hat{\alpha}_{1,s}$. I will estimate equation (79) using firm-level sales data. Also, I will use the sales data for firms in the 90th percentile of sales within each sector since the Pareto distribution best fits the right tail of the revenue distribution.[2]

To estimate the elasticity of substitution, I express the sector revenue, R_s in terms of production input expenditures, $wL_s^V = wL_s^p + wL_s^\tau$. From equations (1.21) and the equation for

[1] Recall that the Pareto cumulative distribution for revenues is $G(r_{i,s}) = 1 - (r_{m,s}/r_{i,s})^{\theta_s/\sigma_s - 1)}$.

[2] Using the upper tail for estimating the shape parameter follows **?** The reason is that the relationship between firm rank and size is approximately linear for the group of firms in the upper tail of the distribution (**?**).

$L_s^p + L_s^\tau$ in Appendix C.4, I express revenue as follows:

$$R_s = \frac{\sigma_s}{\sigma_s - 1} w L_s^V \tag{46}$$

where revenue refers to the sector's inventory-adjusted aggregate value of sales in the fiscal year of 2004, and expenditures on production input, wL_s^v, includes all factor payments such as wages, energy, and raw material for a plant in 2004.

F Relating the Model to the Emission Decomposition Components

From Appendix **??** I can write the following counterfactual proportional changes in emissions:

$$\begin{aligned}\hat{Z}_1 &= \frac{Q_t}{Q_0} = \frac{\sum_s \hat{Q}_{st} Q_{s0}}{Q_0} = \frac{\sum_s (\hat{w}\hat{M}^e_s/\hat{P}_s) Q_{s0}}{Q_0} \\ \hat{Z}_2 &= \frac{Q_t \sum_s \theta_{st} \bar{Z}_{s0}}{Z_0} = \frac{\sum_s \hat{Q}_{st} Z_{s0}}{Z_0} = \frac{\sum_s (\hat{w}\hat{M}^e_s/\hat{P}_s) Z_{s0}}{Z_0}\end{aligned} \tag{47}$$

Using the above equations, I can write the scale, composition, and technique effects in terms of model shocks.

The scale effect measures the impact of changes in aggregate output on aggregate emissions. However, the statistical decomposition approach does not explain the potential influence of environmental regulations and the available abatement technologies on the scale effect. Using the mathematical definition of the scale effect in Appendix **??** I derive the following expression for counterfactual changes in the scale effect:

$$\begin{aligned}\text{Scale eff} &= \hat{Z}_1 - 1 \\ &= \sum_s \hat{Q}_{st} \left(\frac{Q_{s0}}{Q_0}\right) - 1 \\ &= \sum_s \left(\hat{w}\hat{M}^e_s/\hat{P}_s\right)\left(\frac{Q_{s0}}{Q_0}\right) - 1 \\ &= \sum_s (\hat{M}^e_s)^{\frac{\sigma_s}{\sigma_s - 1}} \hat{\varphi}^*_s/\hat{t}_{0,s} \left(\frac{Q_{s0}}{Q_0}\right) - 1 \\ &= \sum_s (\hat{\gamma}^{1/\theta_s}_{R,s}/\hat{t}_s).(1/\hat{m}_s^{(\theta_s\sigma_s/(\sigma_s-1))-1})\left(\frac{Q_{s0}}{Q_0}\right) - 1\end{aligned} \tag{48}$$

The composition effect measures the impact of changes in sectors' output shares on the aggregate emissions. Using the mathematical definition of the scale effect in Appendix **??** I derive the following expression for counterfactual changes in the scale effect:

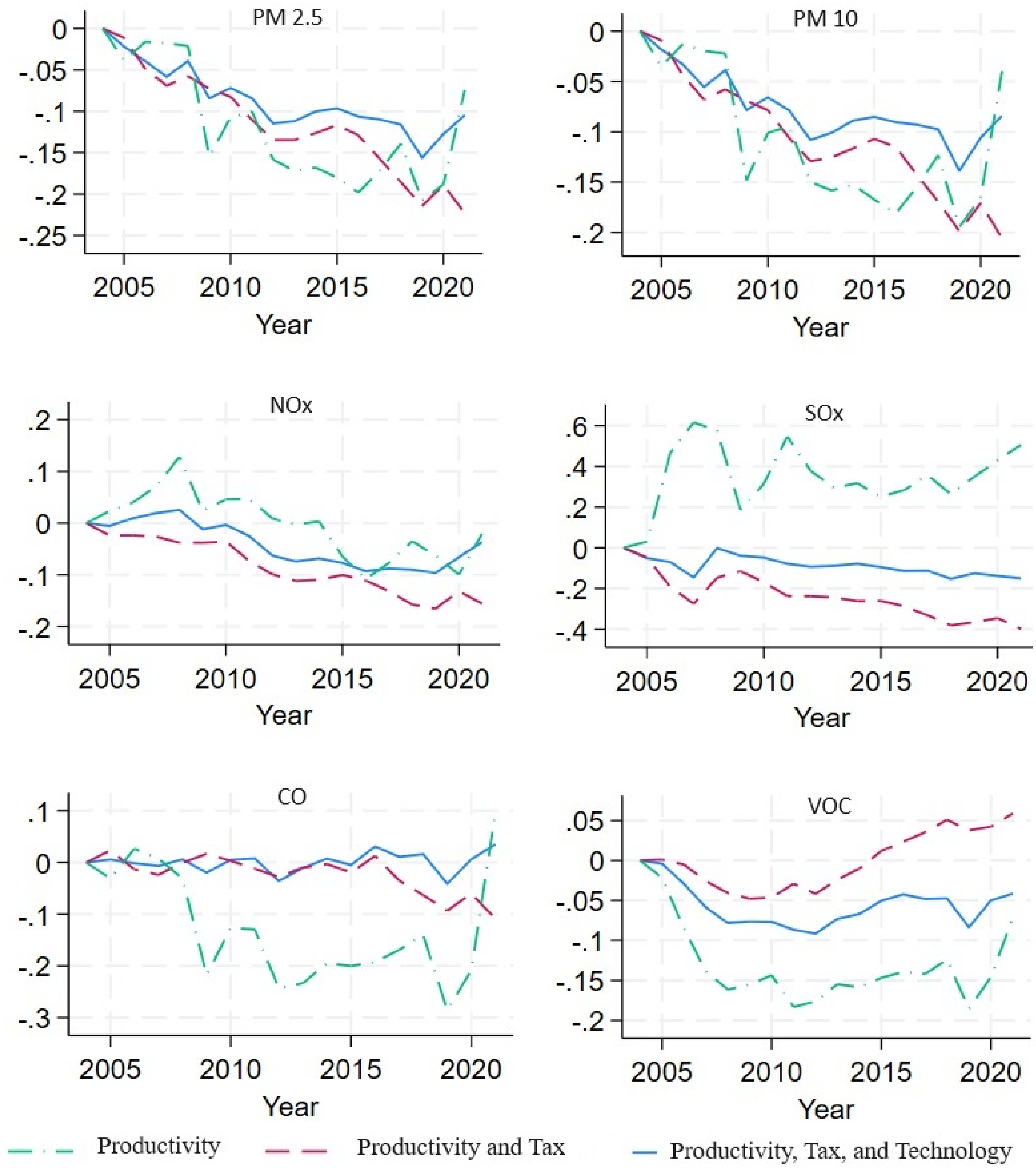
$$
\begin{aligned}
\text{Comp. eff} &= \hat{Z}_2 - \hat{Z}_1 \\
&= \sum_s \hat{Q}_{st} \frac{Z_{s0}}{Z_0} - \sum_s \hat{Q}_{st} \frac{Q_{s0}}{Q_0} \\
&= \sum_s (\hat{w}\hat{M}^e_s/\hat{P}_s) \frac{Z_{s0}}{Z_0} - \sum_s (\hat{w}\hat{M}^e_s/\hat{P}_s) \frac{Q_{s0}}{Q_0} \\
&= \sum_s \left((\hat{M}^e_s)^{\frac{\sigma_s}{\sigma_s - 1}} \hat{\varphi}^*_s / \hat{t}_{0,s} \right) \frac{Z_{s0}}{Z_0} - \sum_s \left((\hat{M}^e_s)^{\frac{\sigma_s}{\sigma_s - 1}} \hat{\varphi}^*_s / \hat{t}_{0,s} \right) \frac{Q_{s0}}{Q_0} \\
&= \sum_s (\hat{\gamma}^{1/\theta_s}_{R,s} / \hat{t}_s)(1/\hat{m}_s^{\theta_s \sigma_S / (\sigma_s - 1) - 1}) \frac{Z_{s0}}{Z_0} - \sum_s (\hat{\gamma}^{1/\theta_s}_{R,s} / \hat{t}_s)(1/\hat{m}_s^{\theta_s \sigma_S / (\sigma_s - 1) - 1}) \frac{Q_{s0}}{Q_0} \qquad (49)
\end{aligned}
$$

Finally, the technique effect measures the effect of changes in the sectors' emission intensities on the aggregate emissions. This effect is the one that is attributed to the environmental regulations in many studies. Using the mathematical definition of the scale effect in Appendix **??** I derive the following expression for counterfactual changes in the scale effect:

$$
\begin{aligned}
\text{Tech. eff} &= \hat{Z} - \hat{Z}_2 \\
&= \sum_s \left(\hat{Z}_{st} - \hat{Q}_{st} \right) \frac{Z_{s0}}{Z_0} = \sum_s \hat{M}^e_s \left(1/\hat{T}_s - \hat{w}/\hat{P}_s \right) \frac{Z_{s0}}{Z_0} \\
&= \sum_s \frac{1}{\hat{m}_s^{\theta_s}} \left(\frac{\hat{\gamma}_{Z,s}}{\hat{t}_s \hat{\gamma}_{R,s}} - \frac{\hat{\gamma}^{1/\theta_s}_{R,s}}{\hat{t}_s \hat{m}_s^{(\theta_s - \sigma_s + 1)/(\sigma_s - 1)}} \right) \frac{Z_{s0}}{Z_0} \qquad (50)
\end{aligned}
$$

Figure F.1 depicts the time trajectories of the composition effect under three distinct counterfactual scenarios, as presented in equation (1.40). The solid blue line represents the actual historical composition effect, which includes productivity, environmental tax, and technological shifts. In contrast, the dashed-dotted green line represents a counterfactual scenario based on productivity shocks and all other factors remaining constant at their 2004 levels. The dashed red line shows another counterfactual scenario based on changes in pro-

Figure F.1: Counterfactual Composition Effects, 2004-2021



Notes: The figure shows the changes in the composition effect over time in three different scenarios. The solid line represents the actual historical composition effect, considering productivity, environmental taxes, and technological shifts. The dashed dot line represents the scale effect if only productivity shocks are considered. The dashed line represents the scale effect if both productivity and environmental tax shocks are considered. All lines are normalized to 0 for the year 2004. Data sources: ASM and NPRI.

ductivity and environmental tax, assuming the sector's technological composition remains unchanged over time. The value is set to zero in 2004, so the graph shows percentage changes in emissions related to counterfactual composition effects.

Apart from CO, changes in the product composition resulted in reduced manufacturing emissions. Specifically, there was a 5% decrease in NOx and VOC, 10% in PMs, and 15% in SOx.

I add another observation to the previous ones from this figure:

Observation F: The gap between the solid blue and dashed red lines shows the secondary regulation effect on the size of the composition effect. The composition effect could have played a more significant role in reducing manufacturing emissions without technological shifts within the sectors. It is important to note that such compositional changes can be very costly for producers. Therefore, the secondary regulation effect made emission reductions more cost-effective by reducing the size of the composition effect.

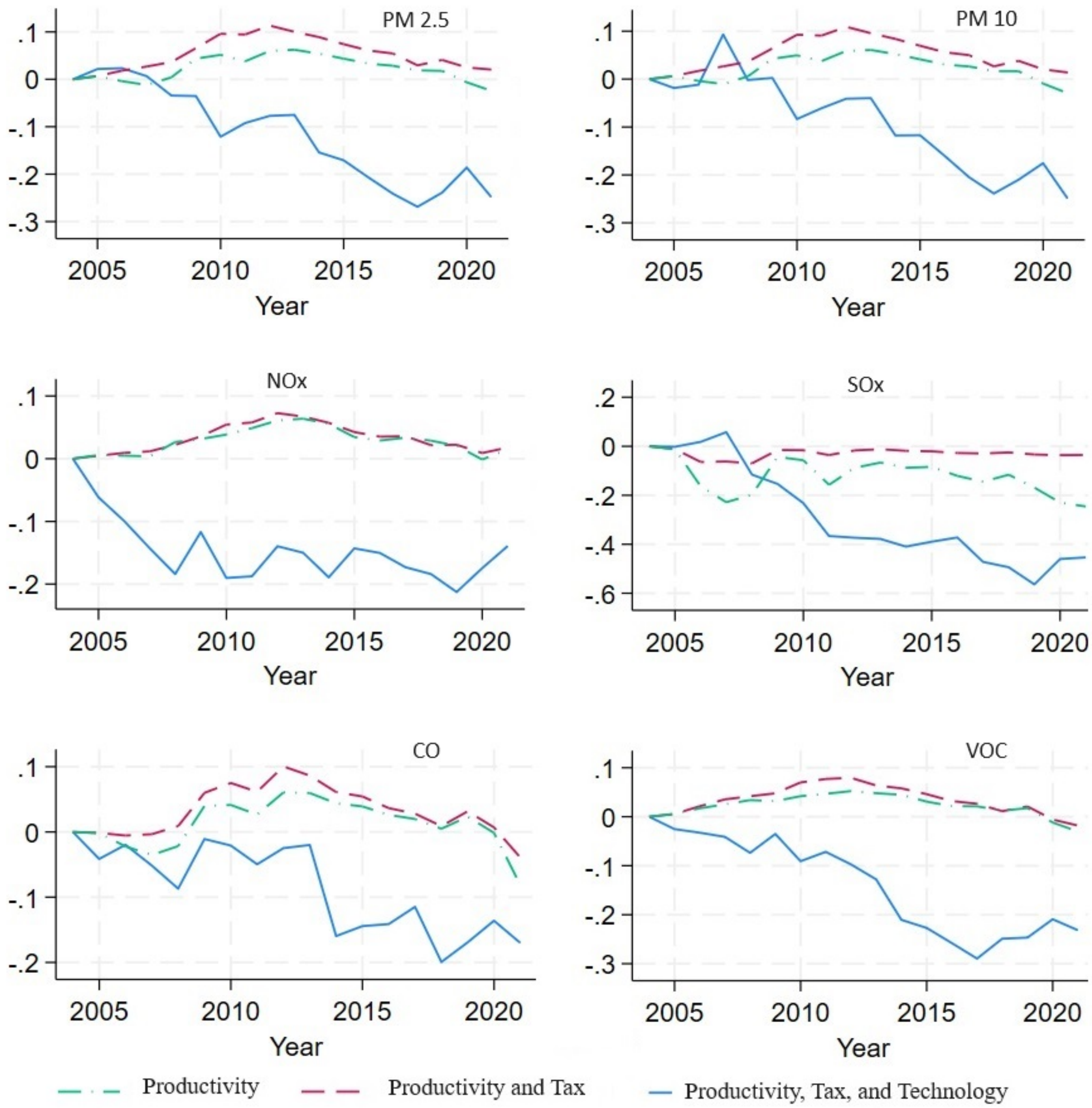
Figure F.2 depicts the time trajectories of the technique effect under three distinct counterfactual scenarios, as presented in equation (1.40). The solid blue line represents the actual historical technique effect, which includes productivity, environmental tax, and technological shifts. In contrast, the dashed-dotted green line represents a counterfactual scenario based on productivity shocks and all other factors remaining constant at their 2004 levels. The dashed red line shows another counterfactual scenario based on changes in productivity and environmental tax, assuming the sector's technological composition remains unchanged over time. The value was set to zero in 2004, so the graph shows percentage changes in emissions related to the effects of the counterfactual technique.

Productivity shocks tend to slightly increase the technique effect for some pollutants (i.e., SOx and CO), but even these small effects are offset by the primary regulation effects.

I add one last observation using this figure:

Observation G: As a general pattern, the primary regulation effect had a very small role in the evolution of the technique effect. Almost all emissions reduction caused by the tech-

Figure F.2: Counterfactual Technique Effects, 2004-2021



Notes: The figure shows the changes in the technique effect over time in three different scenarios. The solid line represents the actual historical technique effect, which takes into account productivity, environmental taxes, and technological shifts. The dashed dot line represents the scale effect if only productivity shocks are considered. The dashed line represents the scale effect if both productivity and environmental tax shocks are taken into account. All lines are normalized to 0 for the year 2004. Data sources: ASM and NPRI.

nique effect comes from the secondary regulation effect. Had it not been for the flexibility provided by abatement technologies in the sectors, we would not observed any technique effect in manufacturing clean-up.

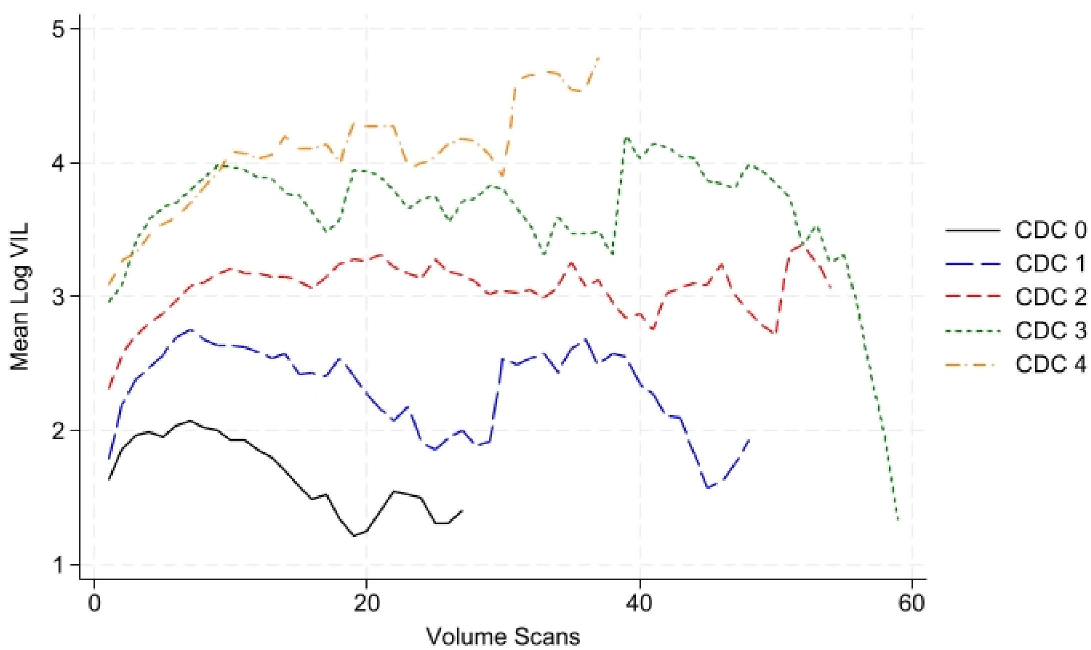
G Descriptive Statistics of Storm Tracks

Table G.1: Descriptive Statistics of Storm Tracks

Statistic	Mean	Std. dev.	Min.	Max.
Track VIL	27.12	24.87	0.96	198.16
# of Volume Scans per Track			15	67
Track Duration (minutes)	112.31	49.54	60	268
Track location – Longitude	-114.32	0.57	-115.76	-111.63
Track location – Latitude	51.64	0.60	50.29	53.05
Max Track VIL	50.27	34.30	1.39	198.16

Figure G.1 depicts the average patterns of storms' evolution classified based on the CDC index, and Table I.1 illustrates a hypothetical storm pattern used in analyzing the IRFs.

Figure G.1: Storms' Average Log VIL Over Time by CDC Index



H The Current Policy Details

The current seeding policy is to start seeding storms as they enter the hail suppression zone. Table **??** shows the likelihood of seeding based on the storm's intensity at the time of seeding. The likelihood of seeding is increasing as the storms intensify. Half of the volume scans in the fourth quartile, close to the maximum VIL, are identified as seeded.

Table H.1: Probability of Observing Seeding Activity in the Proximity of Maximum VIL

Proximity to Maximum VIL	**Probability of Observing Seeding Activity**
Quartile 1	28.2%
Quartile 2	41.7%
Quartile 3	46.3%
Quartile 4	50.1%

Table H.2 shows the likelihood of scans identified as being seeded (i.e., after 32 minutes) versus the storms' intensity; That is, the storm's intensity when the seeding effect appears. Storms are almost uniformly seeded in all quartiles of maximum VIL.

Table H.2: Probability of Seeded Volume Scans in the Proximity of Maximum VIL

Proximity to Maximum VIL	**Probability of Observing Seeded Volume Scans**
Quartile 1	26.7%
Quartile 2	24.9%
Quartile 3	23.9%
Quartile 4	21.5%

I The pattern of a hypothetical storm

Table I.1: The pattern of a hypothetical storm used in analyzing impulse response functions

T	VIL quartiles
7	1
8	1
9	1
10	1
11	2
12	2
13	2
14	3
15	3
16	3
17	4
18	4
19	4
20	3
21	3
22	3
23	2
24	2
25	2
26	1
27	1
28	1

J Evidence on Porter's Hypothesis

Figure J.1: Evidence for Porter's hypothesis between 2012 and 2019 within four regulated sectors, (2004=0)

Notes: The figure shows that the sector output has increased due to increased implied environmental tax between 2012 and 2019.