Utility Rebates, Emissions Spillovers and Lobbying: Essays on Environmental Economics

by

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Abstract

The first essay, co-authored with Sumeet Gulati, estimates the increase in the market share of ENERGY STAR-qualified appliances attributed to utility rebates in the US. Results show that a dollar increase in the rebate leads to a 0.3% increase in the share of ENERGY STAR-qualified clothes washers while the effect is not significant for dishwashers and refrigerators. Assuming a redemption rate of 40%, the cost of a megawatt hour saved is lower than the estimated cost of building and operating an additional power plant and the average on-peak spot price. Therefore, rebate programs for ENERGY STAR clothes washers are a cost-effective way to reduce energy demand.

In the second essay I analyse the presence of pollution spillovers by looking at emission levels and changes in emissions. I use a spatial autoregressive (SAR) model with geographic distance and industry distance weight matrices as well as an extension of the SAR model that uses the two weight matrices simultaneously to exploit the variation in the toxicity-weighted emission levels and emission changes in a large sample of manufacturing facilities in Canada. I find that, compared to OLS results, these spatial linkages exist and are stronger for within sector linkages than geographic linkages.

In the third essay I use firm-level characteristics to predict the lobbying and abatement decision of firms in a model with two non-cooperating firms. There are three sources of firm heterogeneity, viz. the marginal cost of production, the emission intensity and the marginal cost factor of abatement. The decision to lobby or abate or do both depends on the cost-effectiveness of lobbying against that of abating. I find that a firm will abate and not lobby if its effective marginal abatement cost, which depends on output, is lower than a threshold value.

Preface

Utility Rebates for ENERGY STAR Appliances: Are They Effective? is a manuscript co-authored with Prof. Sumeet Gulati. Souvik Datta is the primary author in all regards. The identification and design of the research program for this paper were carried out jointly. Background research, the data analysis, and the preparation of the manuscript were performed by Souvik Datta, with comments on revisions provided by Prof. Sumeet Gulati.

Chapter 2 of the thesis, Utility Rebates for ENERGY STAR Appliances: Are They Effective? (Datta and Gulati, 2010), has been submitted for publication.

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Acknowledgements

Writing a thesis is a long and, at times, arduous process. I would not have made it this far without the help and advice of a number of people. First, and foremost, my co-supervisor, Prof. Werner Antweiler. I would like to thank him for the time and effort he has put in to provide guidance and stimulate my interest in a variety of topics that I have worked on. I would also like to extend my thanks and gratitude to Prof. Sumeet Gulati for co-authoring one of the chapters with me. I have learnt a great deal from his constant feedback and suggestions. Writing a paper with him has been an extremely fruitful and rewarding experience. I would also like to thank my other co-supervisor, Prof. Shinichi Sakata, for his suggestions and prompt response to any of my queries. I would also like to thank all my colleagues who attended my seminars and presentations and provided invaluable suggestions.

My biggest gratitude goes to my parents, Prof. Subir Datta and Mrs. Rina Datta. They are the two people in my life who have been there constantly, albeit half a world away during my years of graduate study. They have always encouraged me in my endeavours and they are the inspiration behind my decision to pursue a doctorate. I cannot thank them enough or ever repay them for being the most wonderful parents one could have wished for. I love them and will eternally be grateful to them. I have, probably, never thanked them for all that they have done for me and their sacrifices but that has, hopefully, been rectified. It is their constant support and encouragement that has seen me through. It is for all those reasons and many, many more that this thesis is dedicated to them.

To Ma and Baba

Chapter 1

Introduction

This thesis deals with three separate issues in environmental economics. The first essay is about the effectiveness of utility rebates on the purchase of energy-efficient appliances. The second essay uses spatial econometric methods to investigate spillovers that may exist in pollution emissions. The third and final essay utilizes a theoretical model to make predictions about the decisions of heterogeneous firms to lobby or abate or do both.

It is now widely accepted that anthropogenic greenhouse gas (GHG) emissions are the main cause of climate change. The energy sector accounts for approximately 65% of our output of GHGs (International Energy Agency, 2009) and thus reducing emissions in this sector is a crucial element of GHG reduction. To reduce GHGs increasing energy efficiency is considered a "low-hanging fruit" because of its low marginal cost. The World Energy Outlook 2009, published by the International Energy Agency (IEA) highlights the huge potential of CO_2 reductions from increased energy efficiency (see Figure 1.1). In the first essay we analyse a policy used to encourage the adoption of energy efficient appliances and thus lower the demand for electricity.

Federal and local governments and utility companies across the United States and Canada promote the adoption of energy efficient appliances identified by a voluntary eco-labelling program, the ENERGY STAR label, by offering financial incentives. The ENERGY STAR label is designed to promote the use of energy-efficient products and thus help to reduce the emissions of greenhouse gases by reducing energy consumption. These incentives are usually in the form of rebates or sales tax holidays. The adoption of energy efficient appliances has public (reduced GHG emissions) and private (saving in utility bills) benefits.[1] In this essay we ask two questions, what is the sales impact

[1] According to calculations made by D&R International Ltd. the lifetime cost for clothes washers, using the product database from 2007, was US$1,883 for a standard model and US$1,726 for an ENERGY STAR model. While the median purchase price for a standard model (US$573) was much lower than an ENERGY STAR model (US$966)

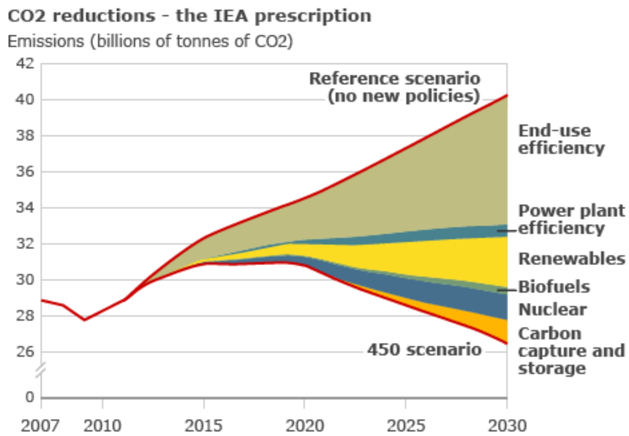

Figure 1.1: World Energy-related CO_2 Emissions Abatement (Source: IEA)

of these rebates? Is it cost effective for a utility company to offer a rebate to its consumer to buy an Energy Star labelled appliance?

Our research contributes to the the effectiveness of rebate programs in Demand Side Management (DSM) initiatives, research on sales promotions of durable goods and the empirical literature on eco-labelling. There has been, to the best of our knowledge, no research on evaluating the cost-effectiveness of utility rebates to promote the sale of Energy Star appliances.

The rebate programs we study are a part of Demand Side Management (DSM) initiatives undertaken by utility companies initiated in the late 1970s primarily due to the rising gas and oil prices.[2] DSM refers to the "planning, implementation, and monitoring of utility activities designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand" (Energy Information Administration, 2009). Energy-changing and load-shaping objectives are achieved through educating consumers on energy efficiency, promoting energy-efficient products by providing low-interest loans and other financial incentives, controlling load, energy automation and real-time pricing.

The Energy Information Administration (2009) reports that the total actual peak load reduction achieved in 2007 through DSM was 30,276 MW with 58% being attributed to energy efficiency while

the average energy costs for the former were much higher at US$1,310 than the latter (US$760). The underlying utility function in our model is such that the consumer internalizes the net cost savings. The utility rebate will have an effect on the marginal consumer and lead to her purchasing the Energy Star appliance.

[2]See Eto (1996); Nadel and Geller (1996); Nadel (2000) for a history of utility DSM in the US.

the total DSM cost was US$2.5 billion. Gillingham et al. (2006) provide a review of, among other things, DSM activities and report the range of negawatt[3] costs calculated in the existing literature to be between US$8 and US$229 per megawatt hour saved. Loughran and Kulick (2004) claim that DSM effects have been overstated by utilities. However, using the same data Auffhammer et al. (2008) show that the savings reported by utility companies cannot be rejected. A recent paper by Arimura et al. (2009) finds that DSM expenditures over the last couple of decades have cost utilities around US$60 per MWh saved.

Our focus is on a specific component of DSM, the rebate program supporting energy efficient appliances. Revelt and Train (1998) estimate the impact of rebates and loans on the choice of efficiency of refrigerators by residential customers of Southern California Edison (SCE) using stated preference data. They predict that the rebate program has led 8.5% customers to switch from a standard-efficiency refrigerator to a high-efficiency one. They also find that loan programs have a greater impact with 22.6% of buyers switching from standard to high efficiency.[4] Very few studies, though, have looked at the cost-effectiveness of rebate programs in the residential sector. In a survey of the literature on the various kinds of DSM programs Nadel (1992) shows that the cost per kilowatt hour incurred by a utility in rebate programs ranges from low to moderate[5] and is generally between 1.4 cents to 5 cents per kilowatt hour.[6] Nadel (1990) reports the cost to utilities for rebate programs in the commercial and industrial sectors to be US$20-30 per megawatt hour.[7]

Earlier work in marketing focuses on the effects of sales promotions in the nondurable goods and durable goods sector with more focus on the nondurable goods sector. Thompson and Noordewier (1992) investigate the effects of sales promotions on automobile sales of the Big Three automobile manufacturers in the US and find that major year-end promotions using low-rate financing and cash rebates to stimulate sales were effective in 1985 and 1986 but not in 1987.

Research on the Energy Star program has focused almost exclusively on the energy, dollar

[3] "Negawatt" is a term coined by Amory Lovins of the Rocky Mountain Institute to refer to a watt of electricity that does not have to be produced due to an energy saving process in place.

[4] See Train and Atherton (1995) for a similar paper.

[5] This is based on rebate programs for commercial and industrial as well as residential sectors.

[6] US$14 to US$50 per megawatt hour

[7] We hereon, convert all figures originally reported in kilowatt hours to megawatt hours for consistency. 1 megawatt hour = 1,000 kilowatt hours.

and carbon savings or the overall success of the Energy Star program. Howarth et al. (2000) find that the Green Lights and Energy Star Office Products programs have very little effect on the demand for energy but improvements in energy efficiency lead to one-to-one reductions in energy use. In terms of calculating savings estimates, Webber et al. (2000) conclude that 740 petajoules of energy has been saved[8] and 13 million metric tonnes of carbon avoided due to the Energy Star program. In a more recent study, Sanchez et al. (2008) estimate that Energy Star-labelled products have saved 4.8EJ of primary energy and avoided 82Tg C equivalent.[9].

In the second essay I investigate the presence of emission linkages in Canadian manufacturing plants by incorporating spatial effects in my analysis. These spatial effects are the result of spillovers that may occur when the emission of plant i affects that of plant j. I consider two channels of these spillovers and use spatial econometric methods to model this. One channel to measure spatial linkages uses geographic distance while the second channel uses the Standard Industrial Classification (SIC) to measure the similarity in a pair of polluting facilities.

This paper extends the literature in three ways. Firstly, I use the Standard Industrial Classification (SIC) code at the two-digit level to construct a supplementary measure of the closeness of two facilities. The hypothesis being that two facilities with the same SIC code will have a greater similarity in emissions than two facilities with different SIC codes. Previous research has used a decaying function of the Euclidean distance with a single parameter as a measure of closeness. The most commonly used specification is the inverse of the distance squared because of its resemblance to the gravity equation in the trade literature.

Secondly, I simultaneously use the SIC distance as well as the geographical distance in the same specification. This means that the measure of closeness involving the SIC distance captures the effect of plants in similar industries and the proximity measure using the Euclidean distance[10] captures the spatial dependence of facilities that are geographically nearer. Therefore, the two types of spatial dependencies in the dependent variable are separated out by using these two measures of closeness. Using two measures of distance or closeness simultaneously will also enable us to

[8]1 petajoule = 10^{15} Joules. 740 petajoules is equivalent to 205.5×10^6 MWh. 1 MWh = 3.6×10^9 Joules.
[9]1EJ (Exajoule)=10^{18} Joules. 4.8EJ is equivalent to 1.3×10^9 MWh. 1Tg (Teragram) = 10^{12} grams
[10]I use the Haversine formula to measure the orthodromic (great circle) distance between two facilities.

determine the strength and magnitude in the two types of spatial dependencies in the dependent variable.

Thirdly, the data I use is a comprehensive pollution inventory of all manufacturing facilities in Canada. Unlike other studies, this paper includes all the facilities that are required to report to the pollution inventory and is not limited to manufacturing facilities in certain regions. The advantage of using such a comprehensive database, apart from the benefits of having access to more observations, is that we can exploit the various measures of distance, especially the geographic measure by calculating it for all manufacturing facility pairs spread across the country. The standard procedure to measure closeness, as mentioned previously, has been to use a decaying function of the Euclidean distance. If facilities are distant from each other the measure of closeness will, by construction, be very low. In other words, the distance between firms i and j will be very high and, assuming a measure of closeness that is the square of the inverse of the distance, the measure will be very low.

The third essay uses a non-cooperative model with two heterogeneous firms to analyse their decision to lobby or abate or do both. Political lobbying has been an important part of the political scene in the US for a long time. The campaign contributions for candidates running for elections sees millions of dollars being spent, especially during the Presidential race. Apart from these contributions, firms and other organizations have lobbying firms in Washington, DC that lobby the government on various issues including the environment. There are a number of lobbying firms engaged in lobbying for the environment and Superfund.[11] The literature on political lobbying has received a considerable amount of attention especially since the contributions of Grossman and Helpman (1994). The creation of powerful lobbying groups has influenced a wide range of activities ranging from resisting gun control to resisting elimination of trade barriers. Similarly, with regard to environmental regulations firms have taken advantage to lobby the government and resist stricter environmental regulations or to weaken existing ones.

Recently, though, there has been a rise in the literature on corporate environmentalism. This

[11] Superfund is the name commonly given to the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) that was enacted by the US Congress on December 11, 1980 in response to the Love Canal disaster. The law imposed a tax on the chemical and petroleum industries and the revenue was used to create a fund for cleaning up abandoned or uncontrolled hazardous waste sites. The CERCLA was later amended by the Superfund Amendments and Reauthorization Act (SARA) on October 17, 1986. Among other amendments, the size of the trust fund was increased from the $1.6 billion collected under the CERCLA to $8.5 billion.

deals with firms that regulate their pollution on their own free will even when there is no obvious need to. Maxwell et al. (2000) list a variety of reasons why firms would want to voluntarily regulate themselves and reduce pollution. Some of the reasons include reducing consumer uncertainty about product quality and ensuring that products have the same operating standards, increasing employee satisfaction by ensuring a healthy and safe working environment, using self-regulation to soften competition or to preempt government regulation.

There have been a number of papers that have incorporated self-regulation in a model where firms are lobbying for less stringent environmental regulations. Damania (2001) has used a model to explain why old and very polluting firms can often lobby effectively for less stringent environmental regulations and are slow to adopt new and cleaner technologies. He suggests that political considerations may lead to firms rejecting environmentally beneficial investments even though they may lower production costs. Glazer and Janeba (2004) focus on maximization of social welfare rather than on lobbying and find, unlike Damania (2001), that a firm subject to an emissions tax may overinvest in abatement. Maxwell et al. (2000) model self-regulation as a way to preempt government regulation, examine the conditions under which preemption is possible and, if it occurs, examine the welfare consequences.

Chapter 2

Utility Rebates for ENERGY STAR Appliances: Are They Effective?

"Efficiency is the steak. Renewables are the sizzle." – Carl Pope, executive director of the Sierra Club [12]

2.1 Introduction

In this essay we calculate the impact of utility rebates on the market share of energy efficient ENERGY STAR appliances. To study the impact of the rebates on the sales of energy efficient ENERGY STAR appliances we use quarterly sales data on the percentage of ENERGY STAR labelled appliances (clothes washers, dishwashers, and refrigerators) for all 50 US states. We combine this with a detailed utility-level, and state level dataset on rebate programs between 2001 and 2006. Our aim is to identify the impact of rebates on sales of ENERGY STAR appliances by correlating differences in the market share of ENERGY STAR appliances with variation in rebate values across and within appliances and across and within US states over time. The panel nature of our dataset allows us to account for changes in purchasing behaviour specific to a single state but invariant over time, or occurring in all states but invariant at a certain time period. This allows us to ensure that we do not attribute state level differences, or national level common time effects to the rebate variable. This is crucial for accounting for sales that would have occurred even in the absence of utility rebates. Our results indicate that the utility rebates increased the market share of ENERGY STAR qualified clothes washers by 4.5%. We also find that the utility rebates had no

[12] Wald (2007)

impact on the sales of dishwashers and refrigerators.

We use the above estimates to evaluate the cost of a tonne of carbon emissions saved as well as the cost of a megawatt hour saved. The former cost calculation will enable us to compare the cost with that of the social opportunity cost of carbon while the latter cost can be informative in comparing with the cost of constructing and operating a power plant or the average price of additional electricity bought in the spot market. The cost of reducing a tonne of carbon, depends on the assumption for redemption rates of mail-in rebates(the main avenue for these rebates), and ranges from US$171 to US$426. We also calculate the cost of a megawatt hour saved due having the rebate programs in place for comparisons with the estimated cost of building and operating a power plant as well as the cost of on-peak spot prices. Given the assumption of a 40% redemption rate on mail in rebates, the cost of a megawatt hour saved is around US$35 which is significantly lower than the cost of constructing and operating the cheapest power plant.[13] Average on-peak prices at US$60 are also higher than the cost of rebate programs which means that buying electricity in case demand exceeds supply is more expensive than reducing electricity demand through increased efficiency.

The rest of the chapter is organized as follows. In the next section, we provide an overview of the ENERGY STAR program. We then discuss the rebate programs offered by utility companies in section 2.3 and follow it up with a description of the data, its sources and limitations in section 2.4. The empirical strategy is laid out in section 2.5 and the econometric results are discussed in section 2.6. The penultimate section in this chapter uses the results from our regression model to calculate the energy saving and cost of having the rebate programs in place while the final section has concluding remarks.

2.2 A Brief Overview of ENERGY STAR

The ENERGY STAR program was introduced in 1992 by the United States Environmental Protection Agency (EPA) as a voluntary labelling program designed to promote the use of energy-efficient

[13]The cost of a coal-fired power plant, according to Du and Parsons (2009), is the lowest at US$62 per megawatt hour.

products and thus help to reduce the emissions of greenhouse gases. Its mission is to set standards for the ENERGY STAR label; label energy-efficient products; provide objective information to consumers; work with national, regional and local groups to promote energy efficiency; and lower the costs of owning energy efficient equipment and products through alternative financing. The US EPA, in 1991, had already introduced another eco-labelling program, the Green Lights Program, which was a partnership program designed to promote efficient lighting systems in commercial and industrial buildings. This was integrated into the ENERGY STAR program for buildings in 1995.

The ENERGY STAR program, which had been administered exclusively by the US EPA since its beginning, became a partnership of the EPA and the US Department of Energy (DOE) in June, 1996. The ENERGY STAR label for dishwashers, refrigerators and room air-conditioners (RACs) was announced in October, 1996. Clothes washers were included in July of the following year. The label is now displayed in over 50 product categories including major appliances, office equipment, lighting, home electronics and other products. It also covers new homes and commercial and industrial buildings.

In this chapter we focus on the ENERGY STAR program for clothes washers, dishwashers and refrigerators. More details about the ENERGY STAR program for these particular appliances are provided in Appendix A. These appliances markets have traditionally been quite stable (Paton, 2005) as can be seen in Figure 2.1 where the quarterly unit shipments of clothes washers shows a very gentle upward trend. The figures for ENERGY STAR qualified clothes washers, however, show a very strong upward trend. In terms of the share of the market, ENERGY STAR qualified clothes washers have increased from 10% in 2001 to almost 38% in 2006. The picture looks even more drastic for dishwashers with ENERGY STAR qualified dishwashers having captured a little more than 92% of the market in 2006 as compared to around 10% in 2001 (Figure 2.1). Figure 2.2 shows the fraction of ENERGY STAR qualified dishwashers, clothes washers and refrigerators from 2001 to 2006. It shows the stark contrast in the penetration of ENERGY STAR qualified dishwashers as compared to clothes washers and refrigerators.

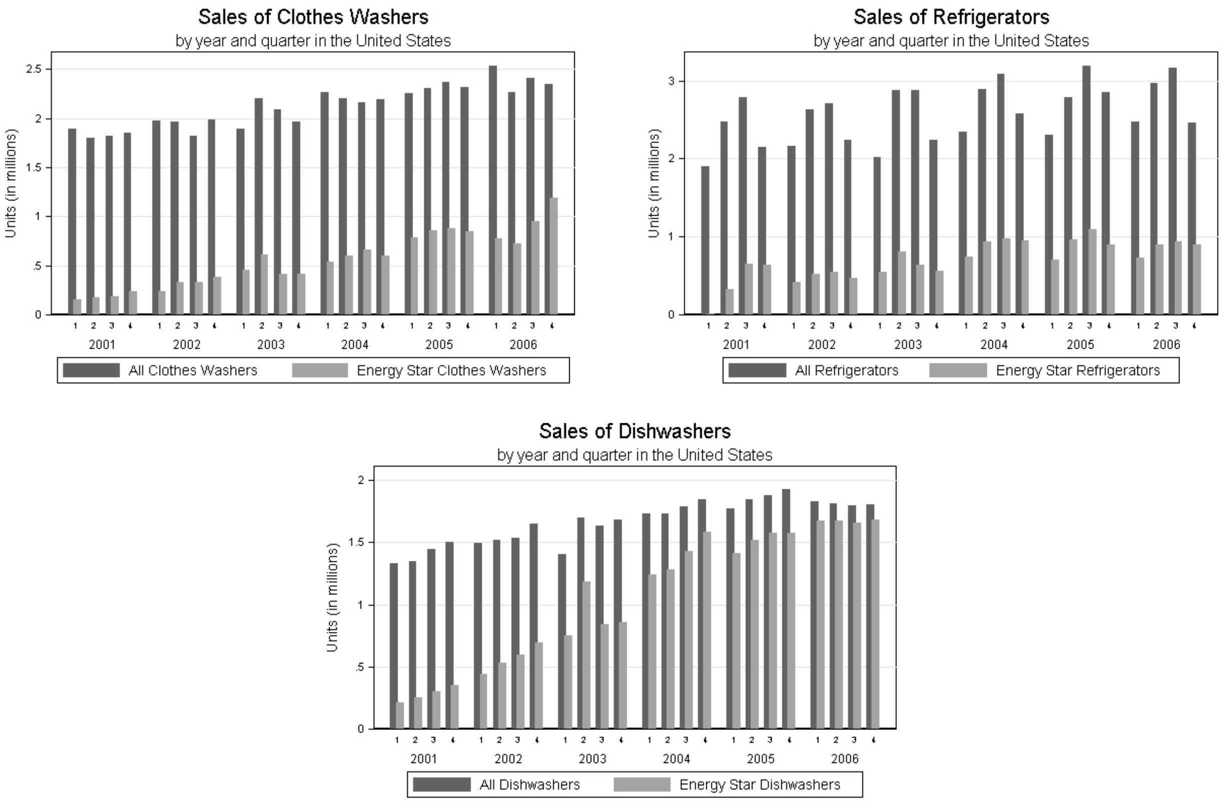

Figure 2.1: Sales of Clothes Washers, Refrigerators and Dishwashers (Source: Appliance Design (various years) and ENERGY STAR)

2.3 Utility Rebates

US states and regional utility companies encourage consumers to switch from standard appliances and other electric products to more energy and resource efficient ENERGY STAR products using several types of financial incentives (for example: mail in or instant rebates, or tax credits and exemptions). Of these the most popular are mail-in and instant rebates. Rebates are meant to help consumers overcome the initial cost of buying and installing a higher-priced energy-efficient appliance.

Regional utility companies have supported the purchase of ENERGY STAR appliances almost since the beginning of the ENERGY STAR program for appliances. In 1998, in the Northwestern United States ENERGY STAR qualified clothes washers were promoted through rebates and incentives offered by the Northwest Energy Efficiency Alliance. Supplemental rebates and financing

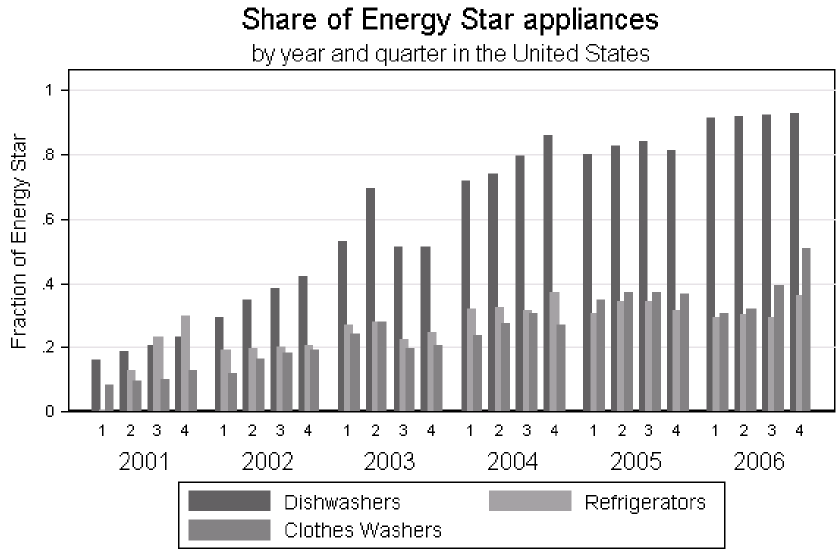

Figure 2.2: Share of ENERGY STAR qualified Dishwashers, Clothes Washers and Refrigerators (Source: ENERGY STAR)

was offered by a number of utilities in Washington, Oregon, Montana and Idaho (Energy Star Sales Report, 1999). Similarly, most utility companies in California and several utility companies in New England (through the Northeast Energy Efficiency Partnerships, Inc.) and Wisconsin also supported the sale of ENERGY STAR appliances (Energy Star Sales Report, 1999). The same regions experienced a much larger penetration of ENERGY STAR qualified clothes washers than other regions.

While the savings to consumers, in terms of lower utility bills, are quite obvious there are a number of reasons why utilities would want to promote the use of ENERGY STAR products.[14] It is argued that promoting energy efficiency costs less than building brand new power plants. There are also environmental reasons. Utility companies need to follow a number of environmental regulations. There are emissions control strategies in place and saving energy on the margin will allow the more polluting plants to be removed from producing electricity. Lastly, the California electricity crisis of 2000 and 2001 showed that reducing peak demand combined with reducing

[14]Benefits to consumers can be seen by comparing the average energy use of an ENERGY STAR and a non-ENERGY STAR qualified appliance. See tables 2.7 and A.5 for information on the energy used by an average ENERGY STAR versus an average non-ENERGY STAR clothes washer and dishwasher and refrigerator respectively.

energy demand can lead to grid reliability.

2.4 Data Description

We use data from a number of sources. The sales data of ENERGY STAR-qualified appliances are from the US Department of Energy (2008a). Information about the utility rebates on ENERGY STAR products is from D&R International Ltd. Demographic data come from the Current Population Survey, the Bureau of Economic Analysis and the US Census. Electricity price data are from the Energy Information Administration of the US Department of Energy.

2.4.1 Energy Star Sales

The ENERGY STAR website has data on sales of the four major appliances, viz. clothes washers, dishwashers, air conditioners and refrigerators. The data are disaggregated by the type of major appliance in each US state by quarter from 2001 to 2006. We exclude air conditioners in our analysis due to missing data. Sales of appliances are categorized into ENERGY STAR and non-ENERGY STAR units. The appliance manufacturers report the sale of ENERGY STAR units to the US EPA every year. For obtaining sales figures of non-ENERGY STAR units the EPA uses the difference of the sales figures of total ENERGY STAR units sold and the total US sales obtained from industry reports.

2.4.2 Utility Rebates

Financial incentives are in the form of rebates that vary in amount as well as form across utility companies and across different appliances. For example, in 2006, the City of Lompoc Utilities in California offered a rebate of US$120 on ENERGY STAR qualified clothes washers paid as a US$10 per month credit on a consumer's utility bill. In another example, also in 2006, customers of National Grid in Massachusetts were given a US$100 either at the time of purchase or as a mail-in application.

Information about rebates and incentives provided by utilities between 2001 and 2006 was

Table 2.1: Number of Utility Rebates for Energy Star Appliances (2001–2006)

State	Clothes Washers	Dishwashers	Refrigerators
California	28	23	36
Colorado	8	1	2
Connecticut	6	0	3
Iowa	12	11	13
Idaho	12	8	5
Illinois	2	0	0
Massachusetts	21	2	0
Minnesota	19	6	7
Missouri	1	0	0
Montana	7	6	6
New Hampshire	8	0	0
Nevada	10	3	8
New York	2	0	0
Oregon	51	35	30
Rhode Island	3	0	0
South Dakota	2	0	0
Texas	0	0	1
Utah	0	0	1
Washington	60	26	21
Wisconsin	2	2	3
Wyoming	1	1	1
Total	255	124	137

Note: Numbers indicate total number of utility rebates offered.

obtained from D&R International Ltd. This includes details of the incentive type, the program name, the amount of rebate offered, a summary of the rebate with the period of time the rebate is offered and the appliances or products to which the rebate applies. Table 2.1 provides details on the number of utility companies providing rebates to its customers from 2001 to 2006 for various appliances. Rebates are concentrated mostly in the northwestern states and California as well as northeastern states. We have considered only mail-in and instant rebates that constitute 91% of the total incentives on offer. Our dataset has a total of 602 financial incentives out of which 546 are mail-in and instant rebates. Of those, 95% are mail-in and 5% are instant rebates. Table 2.2 provides a detailed breakdown of the various types of financial incentives offered by utility companies. Figure 2.3 shows the rebate amounts and corresponding frequencies in our sample. Most of the rebate amounts have a US$50 or US$100 value for clothes washers. Rebates for dishwashers and refrigerators in our sample are typically US$25 or US$50.

Table 2.2: Types of Financial incentives Offered by Utility Companies (2001–2006)

Type of Dollar Incentive/Rebate	Frequency	Percent
Instant Rebate (at point of sale)	14	2.56
Instant Rebate (as credit on bill)	15	2.74
Mail-in Rebate	517	94.69

The disadvantage of not having sales figures by smaller geographic entities is that rebates provided by utility companies are local in nature and, usually, do not apply to the entire state. That leads to an aggregation problem when we are trying to estimate the effectiveness of rebates on the sales of ENERGY STAR units for the state as a whole. Consider a situation where we have rebates in two states with a similar population, and preferences. The rebates are assumed, for the sake of simplicity, to be of equal value. However, the extent of the rebates differ with one state having it in, say, just one county served by a utility company and the other state having it in many more counties. This should not lead to the same effect on the state-wide sales share of ENERGY STAR appliances. In this situation we would expect the latter of the two states to have a bigger impact on the sales share. To rectify this we assign weights to the rebates. The weights that we use are the share of the residential customers served by the utility company providing the rebate to the total number of residential customers in a state. The number of customers served by each utility company are from the Energy Information Administration (2006) of the US Department of Energy. Using weighted rebates means that utilities serving a larger customer base will have higher weights assigned to their rebates.[15]

2.4.3 Demographic and Electricity Data

We use state quarterly income estimates from the US Bureau of Economic Analysis to measure income. Personal income is the income received by all persons from all sources. It is therefore a

[15]Our preferred specifications use weighted rebates. However in the text we also report results from using a simple average of utility rebate offered. We have also analysed the impact of utility rebates after controlling for state level sales tax rebates on ENERGY STAR appliances. Unlike the utility rebates, which last typically for an year or more, most state level rebates typically lasted for a few days during a year. These results are not reported in the thesis and can be requested from the authors. We find that the results of regressions controlling for the sales tax rebate are essentially the same as those reported here. Coefficients on the sales tax rebates are not significant. This is because these rebates were in place only for a few days and we use quarterly sales data making it hard to identify their impact.

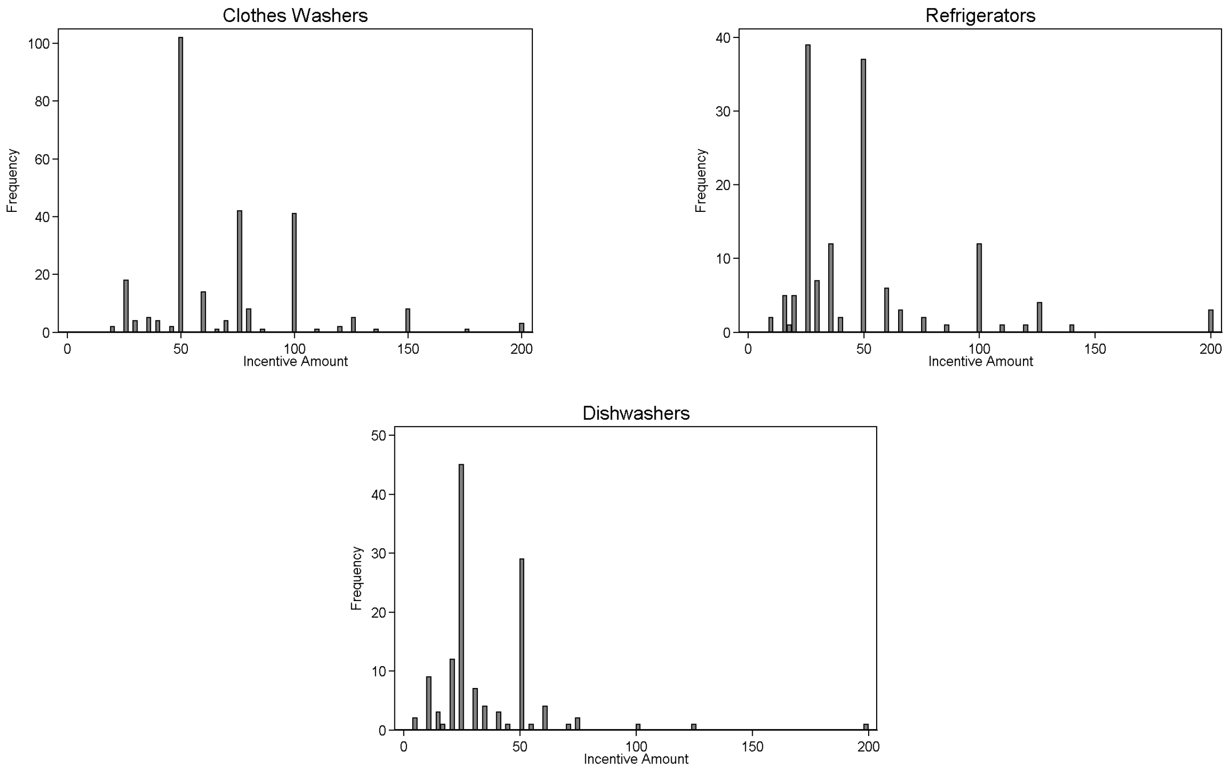

Figure 2.3: HISTOGRAM OF ENERGY STAR REBATE AMOUNTS (2001–2006)

good measure of the average wealth. The CPS is a monthly household survey conducted by the Bureau of Labor Statistics to measure participation and employment of the US labour force. The CPS has details on the highest level of education obtained. We construct a measure of education, 'Having a degree', that gives us the fraction of people in a particular US state to have completed a degree of any kind.[16]

Electricity prices are from the (Energy Information Administration, 2008) of the US Department of Energy. We calculate the quarterly price for each state from 2001 to 2006 using the monthly retail price for electricity in the residential sector.

[16] Associate Degree-Occupational/Vocational, Associate Deg.-Academic Program, Bachelor's Degree(ex: BA, AB, BS), Master's(ex: MA, MS, MEng, MEd, MSW), Professional School Deg(ex: MD, DDS, DVM) or Doctorate Degree(ex: PhD, EdD).

Table 2.3: SUMMARY STATISTICS (2001–2006)

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Clothes Washers Share	0.274	0.138	0.026	0.842	1200
Log of Clothes Washers Share	-1.460	0.626	-3.663	-0.173	1200
Dishwashers Share	0.607	0.286	0.056	1.000	1200
Log of Dishwashers Share	-0.663	0.641	-2.875	0.000	1200
Refrigerators Share	0.273	0.108	0	0.595	1200
Log of Refrigerators Share	-1.473	0.838	-6.847	-0.520	1199
Log Average Personal Income	11.628	1.055	9.595	14.203	1200
Share of people with degrees	0.317	0.049	0.174	0.468	1200
Log Electricity Price in current quarter	-0.261	0.262	-0.761	0.762	1200

2.5 Empirical Strategy

The timing and size of rebates varies across states and time. We use this variation to estimate the impact of the utility rebates on the sales of ENERGY STAR labelled clothes washers, dishwashers and refrigerators. In addition there are several states that did not provide any such incentives to its customers. We utilize the panel nature of the data and our dependent variable is the logarithm of the market share of ENERGY STAR appliances. Formally, our empirical specification is:

$$\begin{aligned}\log(\text{ENERGY STAR share})_{cit} &= \beta_0 + \sum_{c=1}^{3} \beta_{1c}\text{Appliance dummy}_{cit} \\ &+ \sum_{c=1}^{3} \beta_{2c}\text{Appliance dummy}_{cit}\text{*Util. Reb.}_{cit} + \beta_3 \text{X}_{cit} + \varepsilon_{cit}, \quad (2.1)\end{aligned}$$

where c is the index for the appliance type (i.e. clothes washer, dishwasher or refrigerator), i is the US state index and t is the year-quarter time index. The β_{2c} coefficients on the right-hand side are our variables of interest since they indicate the effect of the rebate offered on a particular appliance on the market share of that particular appliance. X_{cit} is a vector of controls and ε_{cit} is the standard i.i.d. error term.

This specification enables us to estimate the impact of incentives provided by utility companies as well as control for various other factors that may affect the share of ENERGY STAR appliances.[17]

[17]Note that even though the individual coefficients on the impact of the rebate can differ, our regression pools all three appliances together. This is because we believe that the same underlying utility function determines the choice

A positive estimate for all three β_{2c} coefficients would imply that the rebates are having a favourable impact and that the utility companies are being successful in encouraging people to switch to more energy-efficient technologies. In our set of controls, among other time and state dummies, we also include the fraction of the population having at least a degree, the average personal income (in logarithmic form) for each US State, and the price of electricity. Summary statistics are presented in Table 2.3.

Recall that data on rebates are at the utility level. For our aggregation to the state level we present results of two indicators. We first use the average rebate amount in a state. We construct this by calculating the simple average of all the rebates given by utility companies in a state in a particular quarter for a particular appliance. Our second measure of the utility rebate variable attaches weights to the rebate values. These weights are calculated by dividing the number of residential customers served by the utility company providing the rebate with the total number of residential customers in a state. We do this to ensure that areas with a higher residential customer base in a state have larger weights attached to the utility rebates.

We provide summary statistics of the different rebate measures in Table 2.4. The last column in the table, **Obs.**, indicates the number of data points in our dataset that the rebates imply. For example, there are 239 state-quarter rebates for clothes washers. Since our panel has 50 US states that we track over four quarters for a period of six years between 2001 and 2006 there are 1200 observations for clothes washers alone. For clothes washers, out of those 1200 observations, 239 data points have rebates. The table shows us that the number of utility rebates available for clothes washers far exceeds that for dishwashers and refrigerators. If we consider the average rebate amount and the average weighted rebate amount we see that clothes washers get a much higher rebate amount when compared to dishwashers and refrigerators. The number of rebates as well as the average amount of a rebate is lowest for dishwashers.

We use both fixed and random effects panel data regression models. In the specifications we first observe the effects of the utility rebates on the market share of ENERGY STAR appliances without controlling for any other factors. We then introduce demographic variables, namely the average

between an ENERGY STAR and a non-ENERGY STAR appliance.

Table 2.4: Rebate Statistics for US States Providing Rebates (2001–2006)

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Clothes Washers					
Avg. Rebate Amount	69.699	27.547	25	200	239
Avg. Weighted Rebate Amount	15.215	21.722	0.057	100	239
Dishwashers					
Avg. Rebate Amount	34.746	13.505	10	62.5	158
Avg. Weighted Rebate Amount	1.588	4.365	0.019	35	158
Refrigerators					
Avg. Rebate Amount	50.640	26.324	15	117.5	177
Avg. Weighted Rebate Amount	6.826	15.524	0.022	100	177

personal income (in logarithmic form), the fraction of people having degrees and also electricity prices. In the third specification we interact the appliance dummies with quarter dummies to control for any seasonality that may exist. Lastly, we introduce year-quarter time dummies interacted with the appliance dummies that will capture all changes over time. Since we have state fixed effects in our fixed effects specification introducing year-quarter dummies will take into account most of the variation that may occur. This is, therefore, the most comprehensive and our preferred specification.

2.6 Results

We now present the results of the specifications and describe the methods used to estimate the coefficients. The dependent variable in all the specifications is the log of share of ENERGY STAR appliances. In Table 2.5 the rebate variable we use is the simple average rebate in each state while in Table 2.6 we use our preferred weighted rebate variable.

It is often customary while reporting panel regression results to report the results from the pooled OLS specification. In the interest of preserving space we have left out the pooled OLS results. This is because, the F-test of the null hypothesis that the constant terms are equal across all the states is rejected. In other words, there are significant state level effects which implies that pooled OLS would be inappropriate. In the main text of this chapter (see Tables 2.5 and 2.6) we only present results from a fixed effects panel data specification. The alternative random effects estimation (presented in Tables A.6 and A.7 in Appendix A) assumes the exogeneity of all the regressors with the random individual effects.[18] This is a strong assumption may not be realistic in our case. We use a test for overidentifying restrictions to test for fixed versus random effects and find that the hypothesis of the regressors being orthogonal to the state-level fixed effect is rejected.[19] For this reason the fixed effect specifications is our preferred specification.

The columns FE1, FE2, FE3 and FE4 in Tables 2.5 and 2.6 estimate eq.(3.1) using a fixed effects panel data model. In column FE1 we do not have any controls for demographics or the effect of time. In FE2 we introduce demographics while FE3 includes quarter dummies as well. However, FE4 is the most comprehensive specification with year-quarter time dummies that capture any variation that may exist in all the time periods under consideration. Since we are using market shares of all three household appliances, viz. clothes washers, dishwashers and refrigerators, we have appliance dummies to control for the type of appliance. As mentioned before, the coefficients that are of interest are the ones for the appliance type interacted with the average rebate amount. The baseline is the case where there are no rebates. A positive coefficient for the interaction of appliance type with average rebate amount would indicate a favourable effect on the ENERGY STAR sales share of the appliance due to the rebate.

The results in Table 2.5 and Table 2.6 show that while utility rebates for clothes washers show a positive and significant effect the effect is not the same for dishwashers and refrigerators. The effect, while positive and significant for dishwashers in FE1, FE2 and FE3 loses its significance in FE4. The impact of rebates is not significant for refrigerators. The FE3 specification indicates that the effect is not robust for dishwashers and refrigerators as it is for clothes washers.

We choose the FE4 specification over FE2 and FE3 because it is the most comprehensive specification. If we compare the results from Table 2.6 with those from Table 2.5 where we use the simple average we notice that the results are very similar in terms of their effects as well as significance. Results from our preferred specification, FE3 from Table 2.6 show that a US$1 increase in utility rebates will lead to a 0.3% increase in the share of ENERGY STAR clothes washers but

[18] Random effect models are better suited to estimating models that have time-invariant independent variables. They are also more efficient than the fixed effects.

[19] We use the `xtoverid` command (Schaffer and Stillman, 2006) in `STATA`.

the effect is not significant and robust for dishwashers and refrigerators.

We should note, however, that the average weighted clothes washer rebate is around US$15. Therefore, a US$15 increase leads to a 4.5% in the share of sales of ENERGY STAR clothes washers. We can conclude that the rebate programs have had a positive and significant effect on clothes washers but they have not made much impact for the other appliances.

If we consider other controls in explaining the sales of ENERGY STAR appliances we see that there is a positive effect of average personal income. We expect wealthier people to buy ENERGY STAR appliances since they are, on average, about US$350 more expensive than non-ENERGY STAR models. Our result is similar to that in the literature of tax incentives on the sales of hybrid cars, e.g. in Gallagher and Muehlegger (2008), which have shown that the effect of income is positive. The effect of earnings in our regressions results is positive and significant. We also look at the effect of education on the purchase of energy-efficient appliances. We find that the higher is the fraction of people having a degree in a state the more likely they are to purchase an ENERGY STAR clothes washer. This could be due a greater awareness of ENERGY STAR products and appliances, or a greater concern for the environment. Note that these two effects, become insignificant when we include time dummies. We expect the coefficient for the price of electricity to be positive implying that a higher cost of running appliances would cause people to switch to more energy-efficient ones. This is borne out in our specification. However, on including quarter dummies, this coefficient becomes insignificant.

2.7 Policy Implications

We use estimates from our preferred specification, FE4 from Table 2.6, to examine the effect of utility rebates. Since the coefficient for clothes washers rebates is robust over specifications FE2 to FE3 we only consider clothes washers and exclude dishwashers and refrigerators for calculating the cost of the rebate programs. We first perform a counterfactual exercise in which we assume that none of the states have a utility rebate in place, i.e. $\beta_{2c} = 0$ in Eq.2.1. This gives us the market share of ENERGY STAR clothes washers if no utility rebate had been offered, say $\tilde{y}$. Since

Table 2.5: Regression Models with Average Utility Rebates (2001 – 2006)

	Fixed Effects			
Variable	**FE1**	**FE2**	**FE3**	**FE4**
Intercept	-1.596^a	-48.100^a	-49.672^a	-.990^a
	(.032)	(8.255)	(9.556)	(.020)
CW*Rebate	.978^a	.335^a	.352^a	.245^a
	(.137)	(.072)	(.071)	(.065)
DW*Rebate	1.571^a	.395^b	.437^b	-.379^a
	(.205)	(.179)	(.180)	(.086)
RF*Rebate	1.049^a	.211^c	.205^c	.024
	(.158)	(.112)	(.118)	(.083)
DW dummy	.860^a	1.768^a		
	(.058)	(.546)		
RF dummy	.043	.499		
	(.037)	(.360)		
CW*Log Personal Income		3.848^a	4.035^a	
		(.729)	(.832)	
DW*Log Personal Income		3.864^a	4.051^a	
		(.727)	(.831)	
RF*Log Personal Income		3.859^a	4.047^a	
		(.728)	(.831)	
CW*Education		6.192^a	5.784^a	
		(1.318)	(1.358)	
DW*Education		2.546^b	2.145^c	
		(1.184)	(1.228)	
RF*Education		4.290^a	4.034^a	
		(1.175)	(1.229)	
CW*Log Electricity Price		.441	-.002	
		(.465)	(.598)	
DW*Log Electricity Price		.334	-.099	
		(.483)	(.623)	
RF*Log Electricity Price		.469	-.087	
		(.463)	(.595)	
Quarter dummies*Appliance dummies			Yes	
Year-Quarter dummies*Appliance dummies				Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	3599	3599	3599	3599
Groups	50	50	50	50
R^2	.272	.543	.573	.922
F-statistic	270	362	601	12193

Significance levels : ^{a} : 1% ^{b} : 5% ^{c} : 10%, Standard errors clustered at the state level

Dependent variable is Log (Share of sales of ENERGY STAR Appliances)

Utility rebate amounts re-scaled, CW: Clothes Washers, RF: Refrigerators, DW: Dishwashers

Table 2.6: Regression Models with Average Weighted Utility Rebates (2001 – 2006)

	Fixed Effects			
Variable	**FE1**	**FE2**	**FE3**	**FE4**
Intercept	-1.491[a]	-49.067[a]	-50.440[a]	-.995[a]
	(.029)	(8.247)	(9.568)	(.017)
CW*Rebate	1.250[a]	.331[c]	.340[c]	.308[b]
	(.199)	(.179)	(.175)	(.124)
DW*Rebate	2.132[a]	.977[a]	.989[a]	-.504
	(.583)	(.161)	(.181)	(.402)
RF*Rebate	1.311[a]	-.087	-.086	.206
	(.447)	(.277)	(.237)	(.143)
DW dummy	.823[a]	1.950[a]		
	(.054)	(.558)		
RF dummy	.004	.704[c]		
	(.035)	(.371)		
CW*Log Personal Income		3.927[a]	4.117[a]	
		(.729)	(.833)	
DW*Log Personal Income		3.932[a]	4.122[a]	
		(.728)	(.832)	
RF*Log Personal Income		3.930[a]	4.119[a]	
		(.728)	(.832)	
CW*Education		6.467[a]	6.082[a]	
		(1.342)	(1.378)	
DW*Education		2.595[b]	2.218[c]	
		(1.230)	(1.277)	
RF*Education		4.214[a]	3.933[a]	
		(1.190)	(1.247)	
CW*Log Electricity Price		.449	.010	
		(.476)	(.611)	
DW*Log Electricity Price		.357	-.072	
		(.490)	(.632)	
RF*Log Electricity Price		.537	-.008	
		(.479)	(.616)	
Quarter dummies*Appliance dummies			Yes	
Year-Quarter dummies*Appliance dummies				Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	3599	3599	3599	3599
Groups	50	50	50	50
R^2	.242	.540	.569	.919
F-statistic	377	543	855	5222

Significance levels : [a] : 1% [b] : 5% [c] : 10%, Standard errors clustered at the state level

Dependent variable is Log (Share of sales of ENERGY STAR Appliances)

Utility rebate amounts re-scaled, CW: Clothes Washers, RF: Refrigerators, DW: Dishwashers the estimated coefficient of the effect of the utility rebate variable is positive, the market share for ENERGY STAR clothes washers will be lower than the fitted values using the original estimating equation, say $\hat{y}$. We use the ratio of these fitted values, $\frac{\tilde{y}}{\hat{y}}$ and multiply it with the actual market share to obtain the counterfactual market share if there had been no rebate. The difference between the counterfactual and the actual market shares is the effect of the utility rebates.

We have only yearly sales figures of clothes washers in every US state from 2001 to 2006. However, we do have the quarterly sales figures for the overall US. Therefore, to get an approximate value of the quarterly sales in each state we use the overall US quarterly sales figures over the entire period. This will account for the seasonality in sales that may exist. We use these imputed values to obtain the the increase in the units of ENERGY STAR clothes washers sold in each state, i, in time t given by

$$\mathrm{IUS}_{it} = \mathrm{AUS}_{it} - \mathrm{CUS}_{it} \qquad \text{where } \mathrm{CUS}_{it} = \frac{\tilde{y}}{\hat{y}} * \mathrm{AMS}_{it} \tag{2.2}$$

where IUS_{it} is the increase in units sold of ENERGY STAR clothes washers, AUS_{it} is the actual imputed units sold, AMS_{it} is the actual market share and CUS_{it} is the counterfactual imputed units sold.

The total carbon saving, TCS_{it}, is

$$\mathrm{TCS}_{it} = \mathrm{IUS}_{it} * \Delta\text{Energy Use} * \text{Average Life} * \text{Carbon Emissions Factor} \tag{2.3}$$

where ΔEnergy Use is the difference in the energy use between an average ENERGY STAR and an average non-ENERGY STAR clothes washer. The 'Average Life' is the average lifetime of a clothes washers which is typically 11 years (US Department of Energy, 2008b). Annual estimates of the average energy used by ENERGY STAR and non-ENERGY STAR clothes washers have been obtained from D&R International, Ltd. and are listed in Table 2.7. The figures indicate the average energy consumed in a year under normal usage. We use the carbon emissions factor obtained by Sanchez et al. (2008) to calculate the energy saving. Sanchez et al. (2008) provide the methodology for estimating carbon saving. They first estimate the aggregate discounted energy bill saving using annual average energy prices published by the US DOE. Using carbon emissions

Table 2.7: Average Energy Use of Clothes Washers (in kWh/year)

Year	non-ENERGY STAR	ENERGY STAR
2001	854	290
2002	829	297
2003	829	297
2004	615	254
2005	529	243
2006	531	234

Source: D&R International Ltd.

factors for electricity from the EPA's national average marginal carbon factor they transform the energy saved into the amount of carbon equivalent saved. The EPA's national average marginal carbon factor for electricity is calculated from models required under the UN Framework Convention on Climate Change and historical data from the Emissions and Generation Resource Integrated Database (eGRID) published by the US EPA. Since electricity is generated from both natural gas and oil the carbon factors are assumed to be constant at 13.65 kg C/GJ for natural gas and 18.72 kg C/GJ for oil through the period under consideration. The carbon emissions factor is assumed to be 0.203 kg C/kWh.[20] Therefore, total energy saving are in terms of kg carbon equivalent forgone. We find that the energy saved leads to an equivalent carbon saving of around 78 thousand tonnes.

The total rebate outlay, Total Rebate_{it}, in state i in time t is given by

$$\text{Total Rebate}_{it} = \text{Utility Rebate}_{it} * \text{AUS}_{it} \tag{2.4}$$

where Utility Rebate_{it} is the average weighted rebate amount. This assumes that redemption rate for rebates is 100%. However, according to Spencer (2002), the redemption rate of mail-in rebates for typically high-value products having a high rebate value is around 40%. After accounting for instant rebates we calculate the cost of carbon emissions forgone using both redemption rates to get a range of the cost. A 100% redemption rate on mail-in rebates leads to a rebate spending of US$33.21 million while assuming a 40% redemption rate reduces that figure to US$13.35 million.

[20]The carbon emissions factor has been obtained from the Cadmus Group.

The cost of carbon emissions forgone, Total Cost, is

$$\text{Total Cost} = \frac{\sum_{i,t} \text{Total Rebate}_{it}}{\sum_{i,t} \text{Total Carbon Saving}_{it}} \tag{2.5}$$

Using the figures for the rebate outlay this translates to a cost of US$426 for every tonne of carbon emissions forgone when the redemption rate is 100% while the cost falls to US$171 with the lower redemption rate of 40%. If we compare the cost of reducing a tonne of carbon to the social cost of carbon as estimated by Nordhaus (2007), which is US$17 per tonne, we find that utility companies end up paying much higher for greenhouse gas reductions. However, our lower estimate of US$171 per tonne compares favourably with the larger estimate of the social cost of carbon (US$350 per tonne) obtained by Stern (2007).

There may be concerns of a “rebound effect”. This could happen when the purchase of a high-efficiency clothes washers results in higher usage and, therefore, eliminates the energy saving made by switching from a standard efficiency machine. However, Davis (2008) uses household-level data from a field trial to show that the gains from the energy saving are not offset by higher usage. The field trial in Bern, Kansas (population approximately 200) was conducted to estimate the energy and water savings of h-axis clothes washers by replacing the more inefficient v-axis washers of the participating households (Tomlinson and Rizy, 1998). Davis (2008) estimates a demand function for clothes washing and finds the price elasticity of utilization to be very low at -0.06. We can, therefore, assume that the “rebound effect” is not significant in terms of estimating the energy saving.

As mentioned before, one of the reasons why utilities have Demand Side Management programs, like rebates, in place is to reduce peak demand. For utility companies in a state with very little electricity supply, like California, the cost of buying peak power when demand exceeds supply is very high. The other option is to start peaking plants that are usually natural gas and are very expensive to start up and run. The cost, per megawatt hour, of the utility rebate programs comes to around US$35. This is obtained by multiplying the cost per tonne (US$171) with the carbon

Table 2.8: Costs of Electric Generation Alternatives (US$/MWh)

Type	Base Case	with Carbon Charge US$25/t$CO_2$	with same cost of capital
Nuclear	84		66
Coal	62	83	
Gas	65	74	

Source: du2009update, original values are in cents/kWh.

emissions factor (0.203 kg C/kWh). This cost compares very favourably to the average on-peak spot prices for electricity. Table A.8 shows the figures for on-peak as well as off-peak spot prices at different pricing points. The mean of average on-peak (nominal) prices from 2003 to 2006 is US$60 which is considerably higher than the cost of the rebate programs.[21] The mean of the minimum average on-peak spot prices over the four years, US$48, is also higher than the cost of the rebate programs. We can, therefore, conclude that the rebate program for clothes washers has been successful for utility providers that are looking to reduce the demand for electricity by providing incentives to consumers for switching to more energy-efficient models.

Since utilities are also concerned about the costs involved to build and operate additional power plants we can compare the costs of the rebate programs to that of building one. Du and Parsons (2009) have calculated the cost of electric generation for the three major types of power plants, viz. coal-fired, gas-fired and nuclear. Their calculations, in Table 2.8 are an updated version of the figures published in Deutch et al. (2003). Du and Parsons (2009) find that the cost of constructing and operating a nuclear power plant is highest, at US$84 per megawatt hour. Coal and gas-fired power plants are more cost-effective at US$62 and US$65 per megawatt hour. However, if the social cost of carbon is considered to be US$25 per tonne of CO_2 emitted then the costs rise substantially to US$83 and US$74 for coal- and gas-fired plants respectively. Having utility rebate programs in place are, therefore, a cost-effective alternative to building and running additional power plants.

[21]The mean of average on-peak real prices from 2003 to 2006 is US$57.

2.8 Conclusion

In this essay we have looked at the effectiveness of various financial incentives provided by utility companies on the sales of ENERGY STAR appliances by utilizing the variation in timing and size of the utility rebates across US states. The results indicate that these programs have had a positive and significant impact on the market share of high efficiency clothes washers but not on refrigerators and dishwashers. We find that an increase in a dollar value of rebate leads to a 0.3% increase in the share of ENERGY STAR-qualified clothes washers. Since the average rebate for a clothes washer is around US$15 this translates to a 4.5% increase in the share of energy-efficient clothes washers. In terms of the impact of these rebates in terms of the cost of carbon emissions forgone we find that utility rebates lead to a reduction of 78 thousand tonnes of carbon equivalent. Using the amount spent by utility on providing rebates we find that, over the lifetime of a clothes washer, this leads to a cost of US$171 for each tonne of carbon equivalent emissions forgone. The cost-effectiveness of clothes washer rebate programs in terms of megawatt hour is US$35. Utilities are, therefore, better-off providing incentives to their customers instead of having additional power plants that are costlier to build and operate. This figure is consistent with the cost-effectiveness of DSM initiatives that, according to various authors, range from between US$8.9 and US$253.7.

Chapter 3

A Spatial Econometrics Approach to Analysing Emissions Spillovers

3.1 Introduction

The very nature of pollution is such that it is very rarely confined to a particular area but, depending on the substance and the medium into which it is released, spreads to neighbouring areas. This spatial aspect of pollution is an important consideration when analysing the emissions of firms. The presence of multiple polluting facilities is likely to cause the pollution of the respective plants to be spatially correlated[22], as noted by Gray and Shadbegian (2007). While the environmental performance of a particular plant could be influenced by plant-specific, firm-specific or external factors, they could also be affected by the environmental performance of neighbouring plants (Gray and Shadbegian, 2007). This would lead to spatial dependence in emissions.

There are primarily two questions that this essay endeavours to answer. Firstly, is there any spatial dependency in the emissions of manufacturing facilities? There are many reasons why we would expect spatial dependence to exist. Gray and Shadbegian (2007) mention that the presence of "demonstration effects" would lead to neighbouring plants having similar environmental performance. This is caused by the pressure on a plant to improve on its environmental performance by being in the presence of other better performing plants. This would lead to a positive spatial autocorrelation in the emissions of plants. On the other hand, there could be plants that are dirtier than the surrounding ones. This may be caused by free-riders whereby some plants find

[22]The formal definition of spatial autocorrelation is: $\mathrm{Cor}(y_i, y_j) = \mathrm{E}(y_i y_j) - \mathrm{E}(y_i)\mathrm{E}(y_j), \quad i \neq j$, where the y's are the variable of interest and i and j refer to their respective location.

it may escape attention by being in the midst of better performers as long as they are within compliance. This is likely because the regulatory authorities are concerned about the aggregate level of environmental exposure faced by the population (Antweiler, 2003). So the presence of some plants that are more polluting than others may not be a cause for concern as long as the health of the affected population is not compromised by having a maximum tolerated level of pollution.

Secondly, if there *is* any spatial dependency, what is the channel through which it manifests itself? Is it more pronounced through a simple geographic distance metric? Or are the similarities in the SIC codes more important? There is sufficient evidence to believe that spillovers exist and that these spillovers are greater in magnitude when firms are closer. There could be techonological spillovers so that firms within the same industry have similar equipment or similar pollution abatement technology. In that case we would expect very strong spatial dependence in the emissions of firms in the same sector.

To answer these questions I use data from the National Pollution Release Inventory of Canada published by Environment Canada. This provides data on facility-level emissions. Using the coordinates of the location of the facility, I can obtain the population in the surrounding area from the Gridded Population of the World (version 3) dataset. I also use the US Environment Protection Agency's Risk-Screening Environmental Indicators (RSEI) database (Version 2.0 b2) to calculate toxicity-weighted or health-indexed emissions.

I use various spatial econometric models to analyse the data. The spatial econometric models are based on the parsimonious spatial autoregressive regression (SAR) model. I initially analyse the data using the levels of toxic emissions. I also use the change in emission to study if there is any spatial dependence. Using differences is econometrically superior to using levels since it accounts for fixed effects. After using the two measures of closeness individually, I analyse the data using them simultaneously. I find that, compared to OLS results, spatial dependencies exist and are significant as indicated by the statistical significance of the spatial autoregressive parameters. My results also indicate that the effect of the industry SIC distance is substantially stronger than that of geographical distance.

Methodologically, this essay is closest to Gray and Shadbegian (2007) who use plant-level EPA and Census data from the US to analyse spatial effects that may affect air pollutant emissions and regulatory compliance. In this essay I use a more comprehensive set of manufacturing facilities and an SAR model with two weight matrices simultaneously to extract spatial dependencies affecting air pollutants, total pollutants and air pollutants that are causes of ground level ozone, haze and acid rain.

The rest of the essay is structured as follows. The next section describes the NPRI and population data. Section 3.3 discusses the spatial autoregressive model I will use to measure the pollution abatement spillovers. Spatial and non-spatial regression results and their interpretation are provided in section 3.4. The penultimate section in this chapter discusses the empirical results and their possible causes while the last section concludes.

3.2 Data

3.2.1 National Pollutant Release Inventory

Emissions data is obtained from Environment Canada's National Pollutant Release Inventory (NPRI) that contains publicly available information on the releases and transfers of key pollutants in various communities. The NPRI was established in 1992 and legislated under the Canadian Environmental Protection Act, 1999 (CEPA 1999). Companies are required to report information on releases and transfers of pollutants on an annual basis. However, there are certain reporting criteria for reporting to the NPRI. Pollutants from mobile sources such as trucks and cars, households, facilities that release pollutants on a smaller scale and certain sector activities, such as agriculture and education and some mining activities, are not included in the NPRI but are reported under a separate program. Reporting for each NPRI substance includes an indication of whether the substance was manufactured, processed, or otherwise used and the nature of such activities and uses during a year.

The NPRI is a comprehensive database and also reports the number of employees in each facility as well as the geographic location in terms of latitude and longitude. The number of employees can be used as a proxy for the size of the facility since sales and production data are not available.

Table 3.1: NUMBER OF FACILITIES BY SIC CODES

SIC Code	SIC code Description	Frequency	Percentage
20	Food And Kindred Products	317	10.85
21	Tobacco Products	3	0.1
22	Textile Mill Products	21	0.72
23	Apparel And Other Finished Products Made From Fabrics And Similar Materials	4	0.14
24	Lumber And Wood Products, Except Furniture	359	12.28
25	Furniture And Fixtures	62	2.12
26	Paper And Allied Products	172	5.88
27	Printing, Publishing, And Allied Industries	89	3.04
28	Chemicals And Allied Products	434	14.85
29	Petroleum Refining And Related Industries	55	1.88
30	Rubber And Miscellaneous Plastics Products	238	8.14
31	Leather And Leather Products	1	0.03
32	Stone, Clay, Glass, And Concrete Products	180	6.16
33	Primary Metal Industries	198	6.77
34	Fabricated Metal Products, Except Machinery And Transportation Equipment	282	9.65
35	Industrial And Commercial Machinery And Computer Equipment	67	2.29
36	Electronic And Other Electrical Equipment And Components, Except Computer Equipment	66	2.26
37	Transportation Equipment	178	6.09
38	Measuring, Analysing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks	5	0.17
39	Miscellaneous Manufacturing Industries	192	6.57
Total		2923	100

Geographic coordinates are essential to perform a spatial analysis of the data. I have considered only manufacturing facilities. These are facilities with 2 or 3 as the first digit of their four-digit SIC codes. Table 3.1 shows the breakdown of the facilities in my sample by their two digit SIC codes. I have also considered all the provinces in Canada that have manufacturing facilities. The numbers, by each province, are reported in Table 3.2. As expected, the provinces of Alberta, British Columbia, Ontario and Québec make up the bulk of Canadian manufacturing facilities.

The NPRI is similar to the Toxics Release Inventory (TRI) of the United States Environmental Protection Agency (US EPA). One of the advantages, according to Harrison and Hoberg (1994), of using the NPRI over the TRI is that Canada has followed a policy of negotiations with polluters when it comes to the regulation of toxic substances rather than enforcing the regulations. This considerably lowers the presence of regulatory threat. A weak regulatory threat means that reductions could be attributed to other factors such as, for example, voluntary reductions or technological adoption. Olewiler and Dawson (1998) also report that Canadian manufacturing industries are considerably more polluting than their US counterparts which suggests that Canadian regulations are somewhat more lenient than the US. This, similar to the presence of a lower regulatory threat, is an advantage for studying the impact of voluntary pollution abatement activities since the effect of regulatory intervention, in the Canadian context, should not be very significant. Antweiler (2003) has shown that while the effect of regulatory threat in Canada is statistically significant the magnitude is very small and concludes that it is not a very effective instrument.

I use emissions data from a cross-section of facilities in all the provinces. Table 3.2 shows the number of manufacturing facilities that are located in the respective provinces. Most of the facilities are located in Ontario and Québec with a little more than 70% of all the manufacturing facilities in those two provinces. The time period of the data ranges from 2003 to 2006. While I will be using the average over the 2003 - 2005 period to estimate spatial regressions for emissions levels, I will consider the 2003 - 2006 period for calculating spatial regressions for differences in emissions. This is described in greater detail in the section on empirical strategy. The rationale for this time period is that there were relatively small changes in the chemicals added to the NPRI Substance List. In fact, there were no new chemicals added in 2004 and 2005 after the addition of, mainly, Volatile Organic Compounds (VOCs) in 2003. The addition of new chemicals to the list was also not very drastic in 2006 when only three Polycyclic Aromatic Hydrocarbons and 15 VOCs were added. This relative lack of activity in adding chemicals to the NPRI list, compared to other years, makes this time period especially conducive to studying the emission activities. There were also no modifications to existing substances or to their reporting thresholds between 2003 and 2006 thus ensuring that there would be no compatibility issues.

There are, however, some limitations to using the NPRI data.[23] They include the fact that all emissions are self-reported, not all pollutants of interest are reported and not all sources of pollution are included. Since the emissions are self-reported there is an incentive for facilities to under-report their emissions. However, companies that meet the reporting requirements and fail

[23] See Harrison and Antweiler (2003) for a more detailed discussion of these issues.

Table 3.2: Number of Facilities by Provinces

Province	Frequency	Percentage
Alberta	243	8.31
British Columbia	305	10.43
Manitoba	94	3.22
New Brunswick	45	1.54
New Foundland and Labrador	8	0.27
Nova Scotia	53	1.81
Ontario	1481	50.67
Prince Edward Island	7	0.24
Québec	629	21.52
Saskatchewan	58	1.98
Total	2923	100

to report or under-report their emissions face penalties under CEPA 1999 so a risk for improper reporting does exist.

There are very detailed reports of emissions by polluting facilities. The NPRI reports releases to the air, water and land with emissions being broken down into on-site releases and as well as transfers to off-sites and recycling. I only consider pollutants that were released on-site. Since the majority of the emissions were released into the air I use only on-site air releases as well as total on-site releases. This will facilitate the spatial analysis of any pollution abatement for the air pollutants as well as overall emissions.

A number of chemical pollutants are reported to the NPRI. Emissions of different pollutants cannot, ideally, be treated equally. For example, the health effects of being exposed to one pound of (friable) asbestos is not the same as that of one pound of silver and its compounds. The US EPA has assigned different toxicity scores to the various chemicals in its list to account for the different health impacts. For example, one pound of (friable) asbestos is 10,000 times more toxic than an equivalent amount (by mass) of silver and its compounds when ingested either orally or by inhalation. Therefore, one of the issues concerns the aggregation of various pollutants released in the production process. Instead of using just the total emissions or considering the release of individual chemicals, many authors have used a weighted sum of emissions where the weights reflect the toxicity of the chemicals (see, e.g., Hettige et al. (1992) and Horvath et al. (1995)).

Toxicity scores are obtained from the US EPA's Risk-Screening Environmental Indicators database that provides a list of chemicals as well as their toxicity based on whether they are ingested orally or inhaled. Since the NPRI provides details on the medium into which a particular pollutant was emitted I can construct a toxicity-weighted emissions variable. I use the toxicity scores for inhalation to weight the pollutants emitted into the atmosphere while the values for oral ingestion were used to weight the pollutants emitted into water bodies or the ground.

The variable of interest is the emissions from facilities. To account for the volatility of emissions I calculate the average emissions over three years. The data for emissions levels are averaged over three years from 2003 to 2005 while the emissions data used for analysing differences is averaged over the years 2003 to 2005 and also from 2004 to 2006. I consider three types of emissions to investigate if the spatial dependence varies with the classes of emissions. The first type of emission is a sum of the Criteria Air Contaminants (CACs) that consists of Total Particulate Matter (TPM), sulphur oxides (SO_x), nitrogen oxides (NO_x), VOCs, carbon monoxide (CO) and ammonia. TPM consists of PM_{10} which is Particulate Matter less than or equal to 10 microns and $PM_{2.5}$ which is Particulate Matter less than or equal to 2.5 microns. These CACs, along with some related pollutants, are the causes of air pollution such as smog and acid rain. The second emission variable is the toxicity score-weighted sum of pollutants emitted into the atmosphere while the third variable of interest is the toxicity score-weighted sum of total emissions. As noted in Antweiler and Harrison (2003), the on-site releases of chemicals in the NPRI follows a log-normal distribution. Therefore, the dependent variable in all three cases is the logarithm of the variable of interest.

As mentioned previously, there are various factors that may affect the emissions of a particular polluting facility. One factor may be the presence of a threat of government intervention to regulate emissions. To measure actual threat I use the share of regulated substances as in Harrison and Antweiler (2003). The list of regulated substances is compiled in the *Canadian Environmental Protection Act, 1999* (CEPA 1999) which is an important part of Canada's federal legislation aimed at preventing pollution and protecting the environment and human health. It has several lists that are aimed to prescribe reporting requirements for new substances. Substances that are deemed to be "toxic" under CEPA 1999 are recommended for addition to the List of Toxic Substances

(Schedule 1) of the Act. As mentioned in Harrison and Antweiler (2003), chemicals in the Priority Substances List (PSL) and not in CEPA Schedule 1 can be used to measure the regulatory threat. The reason is that substances are first included in the PSL and then once a decision about the toxicity is reached[24] the substance is included in Schedule 1. However, the PSL has been reduced substantially since many substances are now included in Schedule 1.

3.2.2 Population Data

Population data for Canada is taken from the Gridded Population of the World (GPW) produced by the Center for International Earth Science Information Network (CIESIN) of the Earth Institute at Columbia University.[25] The GPW has taken population data and transformed them into quadrilateral cells at a resolution of 2.5 arc minutes or about 5 km at the equator. The area of the cells depends on the latitude and Deichmann et al. (2001) calculate the cell size to vary from 21 km^2 at the equator to about 15 km^2 at 45°. However, Antweiler (2003) reports that since Canada's population is concentrated mostly in a narrow band between the latitudes of 42° and 53° the change in the size of the cells due to a change in latitude can be ignored.

The location of the facilities from the NPRI database is matched with the GPW data so that each firm is placed in one of the quadrilateral cells. It is very unlikely that facilities are located at the centre of a cell so I take a radius of 2 cells[26] to calculate the population around a particular manufacturing plant. Since the area around each facility is the same the population figures are essentially equivalent to the population densities. While the advantage of using the GPW data is the ability to construct radial areas to approximate the area covered by the emission, the disadvantage is that demographic and socioeconomic data from the Census cannot be matched with those quadrilateral cells. However, there is enough anecdotal evidence that suggests that concerns about "environmental justice" are not a major issue in Canada as it is in the US where research has suggested that demographics do matter (See, e.g., Arora and Cason (1999) and Hamilton (1999)).

[24]The process, as described by Harrison and Antweiler (2003), is not as formal in practice and regulations are introduced only if negotiations about voluntary controls fail.

[25]http://sedac.ciesin.columbia.edu/gpw/

[26]I have used various radii to calculate the population around a facility. Results, although not reported in the essay, show that the estimates are not sensitive to the choice of radius in a particular empirical specification.

Table 3.3: Summary Statistics

Variable	Obs.	Mean	Std Dev	Min	Max
Log of CAC Emissions	2150	17.420	2.685	5.809	25.987
Log of HI Air Emissions	1426	18.941	3.952	1.194	29.972
Log of HI Total Emissions	1641	19.462	4.063	1.194	29.972
Fraction of CEPA-regulated CAC Emissions	2150	0.796	0.316	0	1
Fraction of CEPA-regulated HI Air Emissions	1426	0.627	0.442	0	1
Fraction of CEPA-regulated HI Total Emissions	1641	0.559	0.455	0	1
Fraction of PSL-regulated HI Air Emissions	1426	0.010	0.084	0	1
Fraction of PSL-regulated HI Total Emissions	1641	0.011	0.087	0	1
Log of Employees	2923	4.651	1.187	2.303	8.858
Log of Population	2919	10.344	1.996	2.197	13.473
Δ Log of CAC Emissions	1444	0.016	0.429	-4.615	4.344
Δ Log of HI Air Emissions	816	-0.110	1.092	-9.636	12.184
Δ Log of HI Total Emissions	907	-0.064	1.391	-12.053	16.613
Δ Fraction of CEPA-regulated CAC Emissions	1444	-0.003	0.057	-0.747	0.573
Δ Fraction of CEPA-regulated HI Air Emissions	816	-0.003	0.130	-0.997	1
Δ Fraction of CEPA-regulated HI Total Emissions	907	-0.001	0.138	-0.999	1
Δ Fraction of PSL-regulated HI Air Emissions	816	0.001	0.060	-0.956	0.982
Δ Fraction of PSL-regulated HI Total Emissions	907	-0.001	0.062	-1	0.999
Δ Log of Employees	1637	-0.016	0.212	-6.098	0.658
Δ Log of Population	1611	0.052	0.071	-0.229	0.461

I use the (natural) logarithm of the population figures for 1990 instead of the figure from contemporaneous years. Arora and Cason (1999) note that using demographic characteristics prior to the emissions release data will most likely be exogenous. We can expect that the population figures from 2005 will be affected by the emissions from the corresponding year. However, we can expect the population in 1990 to be exogenous to the emissions between 2003 and 2006. It is possible though, as explained by Arora and Cason (1999), that this assumption does not hold and that there may be some endogeneity bias if people are located in areas based on expectations of how emissions will change after 1990. I also use GPW data from 1995 to calculate the change in the population between 1990 and 1995 and use that in the difference regressions.

3.3 Empirical Strategy

3.3.1 Standard Spatial Models

The spatial dependence of pollution activities may be captured by using spatial econometric methods. The basic assumption of spatial econometrics is that observations are not independent of their location but depend on their neighbouring observations. There are two ways in which spatial dependence can be incorporated in the standard linear regression model. If we need to analyse the existence and strength of the spatial dependence then our variable of interest will have a spatially lagged dependent variable. This is referred to as a *spatial lag* model. There is also a *spatial error* model in which the spatial dependence is incorporated in the disturbance term.[27] Since my concern is the existence and strength of pollution emission spillovers I will restrict myself to the spatial lag model, also known as a mixed regressive, spatial autoregressive model.

The spatial lag model can be written as

$$y = \rho W y + X\beta + \varepsilon \tag{3.1}$$

where y is the emissions (level or differenced) variable, ρ is the spatial autoregressive coefficient, W is the exogenously given $n \times n$ spatial weight matrix, Wy is the spatially lagged emissions variable, X is a matrix of independent (level or differenced) variables and ε is a vector of i.i.d. error terms. The reduced form of Eq. (3.1) is $y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon$ where I is an $n \times n$ identity matrix. The spatial lag term Wy is, therefore, correlated with the error term. This implies that estimating the equation by OLS will be biased and inconsistent. The standard procedure is to use maximum likelihood methods for estimating the unknown parameters. The assumption for the error terms is that they follow a joint normal density function. Under this assumption, the log-likelihood function of the SAR model is:

$$\ln\, L(\beta, \sigma, \rho; y, X) = -\frac{N}{2}\ln(2\pi) - \frac{N}{2}\ln(\sigma^2) + \ln|I - \rho W| - \frac{1}{2\sigma^2}(y - \rho W y - X\beta)'(y - \rho W y - X\beta) \tag{3.2}$$

[27] See Anselin (1988) for the classic text on spatial econometrics. For more recently written introductions to this field refer to Anselin and Bera (1998), Anselin (2001) and LeSage and Pace (2009).

The calculation of the spatial Jacobian would complicate matters but Ord (1975) showed that it can be simplified into a function consisting of the eigenvalues ω_i of the spatial weight matrix as:

$$|I - \rho W| = \prod_{i=1}^{N}(1 - \rho\omega_i) \quad \Rightarrow \quad \ln|I - \rho W| = \sum_{i=1}^{N}(1 - \rho\omega_i)$$

Given ρ, the maximum likelihood estimators of β and σ^2 can be obtained from the first-order conditions from maximizing the log-likelihood function Eq. (3.2). Substituting these values in Eq. (3.2) will give us a concentrated log-likelihood function in ρ. Numerical optimization methods can then be used to obtain a maximum likelihood estimate of ρ. The spatial econometrics toolbox in MATLAB provided by LeSage (1999) has been used to evaluate all these estimates.

One of the critical steps in any spatial regression estimation is the construction of the weight matrix, W. The elements of W give a notion of "distance" between each observation. This "distance" could be either geographic distance or how close one firm is to another with respect to the SIC industry code. To give an example of the latter, one could think of firms with the same industry classification code to be "closer" than firms with different industry classification codes. Geographic distance can be calculated using the Cartesian formula or the more accurate Haversine formula[28]. I use the Haversine formula to calculate the geographic distance between pairs of facilities.

The choice of the appropriate weight matrix to use, W, is also a crucial step. A common way to choose W is to obtain the maximum likelihood values of the different weight matrix specifications and choose the one with the maximum value of the likelihood function. While using the geographical distance as a measure of closeness of the facilities I have used $w_{ij} = d_{ij}^{-1}$ and $w_{ij} = d_{ij}^{-2}$ as the distance between facilities i and j. The diagonal elements, w_{ii} of W are, by convention, equal to

[28] Haversine formula:

$$\begin{aligned}
R &= \text{earth's radius (mean radius = 6,371km)} \\
\Delta\text{lat} &= \text{lat}_2 - \text{lat}_1 \\
\Delta\text{long} &= \text{long}_2 - \text{long}_1 \\
a &= \sin^2(\frac{\Delta\text{lat}}{2}) + \cos(\text{lat}_1).\cos(\text{lat}_2).\sin^2(\frac{\Delta\text{long}}{2}) \\
c &= 2.\text{atan2}(\sqrt{a}, \sqrt{1-a}) \\
d &= R.c
\end{aligned}$$

where the angles need to be expressed in radians.

zero. Using the inverse squared distance specification lends itself to the familiar gravity model in international trade.[29] It also assigns more weight to nearer observations. The weight matrix is also row-standardized with rows summing to one to ensure that the spatial autoregressive parameter ρ lies between -1 and $+1$. This also ensures that the spatial parameter ρ is comparable between models (Anselin and Bera, 1998). I have also used the SIC code to measure the "industrial distance" between plants to see if plants in closer industry classifications have similar abatement activities. Facilities that have the same 2-digit SIC codes have been assigned a distance of zero. For example, $\beta_{ij} = 0$ for two facilities i and j that have an SIC code 20 (Food and Kindred Products). Facilities that do not have the same 2-digit SIC codes but have the same 1-digit SIC code have been assigned a distance of 1 while those with different SIC codes have been assigned a distance of 2. For example, $\beta_{ij} = 1$ for a facility i that has an SIC code of, say, 20 and facility j that has an SIC code of, say, 26. If the 1-digit SIC codes are different, say one facility belongs to SIC code 2 and the other facility has an SIC code of 3 then $\beta_{ij} = 2$. The standard procedure of using the inverse of the SIC distance is not applicable in this case since $w_{ij} = \beta_{ij}^{-1} \to \infty$ and $w_{ij} = \beta_{ij}^{-2} \to \infty$ when $\beta_{ij} = 0$. Therefore, I have considered the elements of W to be $w_{ij} = e^{-\beta_{ij}}$ and $w_{ij} = e^{-2\beta_{ij}}$ where β_{ij} is the difference between the 2-digit SIC code of facilities i and j. This exponential form will ensure that when two plants have the same 2-digit SIC code, w_{ij} is defined and is equal to unity.

The w_{ij} terms should, ideally, be exogenous to the model. However, it may be argued that the location decision of a firm is endogenous. Firms that have a high pollution intensity may be located in non-urban areas while low pollution intensity facilities may be situated in a more urban setting. There may also be zoning restrictions as a form of local regulation that may affect high pollution intensity firms, as discussed in Antweiler (2003). However, using differenced variables should mitigate this problem. By differencing the emission level variable we get the rate of change of emission. This should enable us to deal with the endogeneity of the location decision.

In keeping with standard procedure, I first estimate models using OLS and use the results as a base for comparing the spatial models. With regard to dependent variables, I use the level values to analyse the spatial dependence in the environmental performance but then use the differenced

[29] Results using the inverse distance specification are provided in Appendix B.2.

Table 3.4: LM Lag Statistic Tests for Spatial Dependence

	Levels		Differences	
Dependent Variable	$\mathbf{W_{GEO}}$	$\mathbf{W_{SIC}}$	$\mathbf{W_{GEO}}$	$\mathbf{W_{SIC}}$
CAC Emissions	14.722	292.118	0.060	10.434
	(0.000)	(0.000)	(0.807)	(0.001)
Health-indexed Air Emissions	0.204	57.820	0.234	0.267
	(0.652)	(0.000)	(0.628)	(0.605)
Health-indexed Total Emissions	3.135	230.255	1.329	47.533
	(0.077)	(0.000)	(0.249)	(0.000)

p-Values are in parentheses. Critical χ^2 values for the LM lag statistic tests are 2.71, 3.84 and 6.63 for significance levels 10%, 5% and 1% respectively. $\mathrm{W_{GEO}}$ and $\mathrm{W_{SIC}}$ are weight matrices with $w_{ij} = (\text{geographical distance}_{ij})^{-2}$ and $w_{ij} = e^{-2*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

values to account for any endogeneity in terms of location. Comparing the results of the spatial models with the OLS results provide an indication of how strong the spatial interactions may be. All spatial and OLS regression models are estimated using the Econometrics Toolbox for MATLAB.[30]

3.3.2 Extension of Standard Spatial Models

The standard spatial model Eq. (3.1) can be modified to incorporate spatial regression models with two or more weight matrices. In the previous section I have considered two channels through which pollution spillovers may work, viz. the geographical distance and the SIC code "industry" distance. They were, however, modelled separately. Modifying Eq. (3.1) to incorporate two spatial weight matrices can be used to analyse separate influences in the same model. The extension of the standard spatial model can then be written as

$$y = \rho_{\mathrm{GEO}} W_{\mathrm{GEO}} y + \rho_{\mathrm{SIC}} W_{\mathrm{SIC}} y + X\beta + \varepsilon \tag{3.3}$$

where W_{GEO} is used to capture the effect of geographic distance between neighbouring facilities and W_{SIC} captures the effect of "industry" distance. Compared to Eq. (3.1) the modified SAR model Eq. (3.3) needs a slight modification to find the estimates. The log-likelihood becomes

[30] The Econometrics Toolbox for MATLAB can be obtained at www.spatial-econometrics.com.

$$\ln L(\beta, \sigma, \rho_{\text{GEO}}, \rho_{\text{SIC}}; y, X) = -\frac{N}{2}\ln(2\pi) - \frac{N}{2}\ln(\sigma^2) + \ln|I - \rho_{\text{GEO}}W_{\text{GEO}}\rho_{\text{SIC}}W_{\text{SIC}}|$$
$$-\frac{1}{2\sigma^2}\left(y - \rho_{\text{GEO}}W_{\text{GEO}}y - \rho_{\text{SIC}}W_{\text{SIC}}y - X\beta\right)'\left(y - \rho_{\text{GEO}}W_{\text{GEO}}y - \rho_{\text{SIC}}W_{\text{SIC}}y - X\beta\right) \quad (3.4)$$

where the change in maximum likelihood estimation compared to the standard SAR model is the optimization problem involving the two spatial autoregressive parameters ρ_{GEO} and ρ_{SIC} . The MATLAB functions are obtained from the spatial econometrics toolbox.[31]

The specification with two weight matrices will be useful to test the strength and magnitude of the spatial dependence in emission between facilities that are geographically closer and in the same industry. The spatial dependency arising from the geographical distance is of a (geographically) localized nature in the sense that the emissions of a facility may be affected by the emissions of other facilities that are in its vicinity, irrespective of the industry the other facility belongs to. The other kind of spatial dependency that arises from how close or far apart the facilities are with respect to their respective industries occurs irrespective of geographical factors. While there is no *a priori* reason to rank the strength and magnitude of the two kinds of spatial dependencies we might suspect the latter effect to be stronger than the former.

3.4 Results

3.4.1 Standard Spatial Models

The regression results look at both on-site releases as well as changes in the releases to see if there are any spatial dependencies in emissions. Each table considers a different emissions variable. The first table, Table 3.5, reports the regression results of the aggregation of all the Criteria Air Contaminants. Tables 3.6 and 3.7 contain the regression results of the health-indexed air and total emissions respectively. The results of the estimation procedure for on-site emission levels are given in columns (1), (2) and (3) of Tables 3.5, 3.6 and 3.7. The results for changes in emissions are

[31] The modified MATLAB code for the SAR model with two weight matrices was provided by Donald J. Lacombe.

reported in columns (4), (5) and (6) in each table. The base regression, to which all the other results are compared, is the OLS regression (labelled OLS in each table). Spatial regressions are indicated by $\mathrm{W}_{\mathrm{GEO}}$ and $\mathrm{W}_{\mathrm{SIC}}$ using the geographic and industry distance weight matrices, respectively. The simple SAR model with only one spatial weight matrix is considered initially. The elements of W_{GEO} are the inverse squared distance specification while W_{SIC} is the SIC code industrial distance specification described in the previous section. All OLS, $\mathrm{W}_{\mathrm{GEO}}$ and $\mathrm{W}_{\mathrm{SIC}}$ regressions have province dummies to control for province fixed effects and the OLS and $\mathrm{W}_{\mathrm{GEO}}$ regressions also have two-digit industry SIC dummies to control for industry fixed effects.

The spatial autoregressive coefficient ρ is the parameter of interest in measuring the presence and strength of the effect of neighbouring facilities' emissions and emission changes on the facility under consideration. Most of the spatial regression results show that the spatial dependence in the dependent variable is positive and significant though the strength of ρ depends on the emissions variable as well as the weight matrix considered. While the spatial dependence for CAC emissions is positive but not significant for the emissions variable when we use the geographical distance W_{GEO} as the weight matrix, the effect is positive and highly significant for the SIC distance matrix W_{SIC}. The value of ρ is also positive and very significant for CAC emission changes which suggests that polluting plants that are closer together both in terms of geographical distance as well as SIC codes tend to reduce their CAC emissions together. The magnitude of ρ is, however, lower for changes in emissions when compared to emission levels. Results for health-indexed air emissions are also similar except that ρ is surprisingly negative and significant when we use SIC distance as the spatial weight matrix in the regression for emission differences. This negative spatial dependence suggests that facilities that lower their health-indexed air emissions are surrounded by facilities that increase theirs thus creating a checkerboard-type situation. However, results for health-indexed total emissions show that spatial dependence is positive and significant for both emission levels and changes in emissions. It is negative, albeit insignificant, for changes in emissions when the spatial regression includes the SIC distance weight matrix W_{SIC}.

Results from the spatial regressions show that the coefficients are not too different from the OLS regressions. However, the coefficients from OLS results are less significant than those from

Table 3.5: OLS and Spatial Regression Models for CAC Emissions

Variable	Emission Levels			Emission Differences†		
	OLS (1)	$\mathbf{W_{GEO}}$ (2)	$\mathbf{W_{SIC}}$ (3)	OLS (4)	$\mathbf{W_{GEO}}$ (5)	$\mathbf{W_{SIC}}$ (6)
Intercept	15.510[a]	13.862[a]	2.189	0.099	0.099	0.101
	(0.473)	(0.809)	(1.384)	(0.067)	(0.066)	(0.066)
Fraction of CEPA-regulated output	-1.321[a]	-1.270[a]	-1.509[a]	-2.108[a]	-2.108[a]	-2.109[a]
	(0.153)	(0.155)	(0.148)	(0.112)	(0.112)	(0.112)
Log of Employees	1.000[a]	0.991[a]	0.858[a]	0.521[a]	0.521[a]	0.526[a]
	(0.042)	(0.042)	(0.039)	(0.073)	(0.073)	(0.073)
Log of Population (1990)	-0.174[a]	-0.163[a]	-0.150[a]	0.204	0.204	0.223
	(0.025)	(0.026)	(0.023)	(0.162)	(0.162)	(0.162)
ρ		0.087[a]	0.816[a]		0.001	0.469[c]
		(0.024)	(0.080)		(0.037)	(0.236)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies	Yes	Yes	No			
Adjusted R^2	0.432	0.434	0.346	0.169	0.169	0.169
Observations	2150	2150	2150	2003	2003	2003
Log-Likelihood		-3798	-3891		-402	-401
Spatial Multiplier, $1/(1-\rho)$		1.095	5.435		1.001	1.883

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (CAC Air Emissions). Standard errors are in parentheses.
Specifications $\mathbf{W_{GEO}}$ and $\mathbf{W_{SIC}}$ are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-2}$ and $w_{ij} = e^{-2*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.
†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (4), (5) and (6) should be interpreted as being differences.

the spatial regressions. Including the spatially lagged emission variables in the regressions has the effect of strengthening the effect of the other explanatory variables. However, this effect is not very strong. The regressors across all the regression results tables are common, apart from the fraction of PSL-regulated output in Table 3.5 since none of the CAC substances are present in the PSL. Since the fraction of CEPA-regulated output and PSL-regulated output are a measure of the actual regulation and perceived threat respectively we should expect the effect of these two variables to be negative on the emission level. The higher the regulation or regulatory threat the lower should be the emissions. This prediction holds for the CAC emissions across the OLS and spatial specifications with the effect being slightly lower for the latter (as seen by the lower value) compared to the OLS result. The effect can also be seen in the case of the health-indexed total

Table 3.6: OLS and Spatial Regression Models for Health-Indexed Air Emissions

Variable	**Emission Levels**			**Emission Differences**†		
	OLS (1)	$\mathbf{W_{GEO}}$ (2)	$\mathbf{W_{SIC}}$ (3)	**OLS** (4)	$\mathbf{W_{GEO}}$ (5)	$\mathbf{W_{SIC}}$ (6)
Intercept	16.675^a	16.447^a	4.043	0.044	0.044	0.025
	(0.973)	(1.027)	(2.263)	(0.184)	(0.183)	(0.183)
Fraction of CEPA-regulated output	-2.251^a	-2.248^a	-2.470^a	-3.944^a	-3.944^a	-3.948^a
	(0.222)	(0.220)	(0.201)	(0.195)	(0.194)	(0.194)
Fraction of PSL-regulated output	-4.951^a	-4.942^a	-5.128^a	-5.463^a	-5.463^a	-5.465^a
	(1.072)	(1.060)	(1.066)	(0.529)	(0.527)	(0.526)
Log of Employees	1.077^a	1.076^a	0.980^a	0.376^c	0.376^c	0.377^c
	(0.084)	(0.084)	(0.073)	(0.193)	(0.192)	(0.191)
Log of Population (1990)	-0.241^a	-0.239^a	-0.243^a	-0.726	-0.726	-0.716
	(0.052)	(0.052)	(0.048)	(0.459)	(0.457)	(0.457)
ρ		0.012^a	0.726^a		-0.0003	-0.254^a
		(0.002)	(0.130)		(0.034)	(0.019)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies	Yes	Yes	No			
Adjusted R^2	0.301	0.301	0.262	0.261	0.261	0.261
Observations	1426	1426	1426	1305	1305	1305
Log-Likelihood		-3218	-3250		-1277	-1277
Spatial Multiplier, $1/(1-\rho)$		1.012	3.650		1.000	0.798

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (Health-Indexed Air Emissions). Standard errors are in parentheses.
Specifications $\mathbf{W_{GEO}}$ and $\mathbf{W_{SIC}}$ are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-2}$ and $w_{ij} = e^{-2*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.
†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (4), (5) and (6) should be interpreted as being differences.

and air emissions variables in Tables 3.6 and 3.7.

The change in actual regulation as well as regulatory threat should also have a negative effect on the change in emissions. If the change in regulation or regulatory threat is positive we should expect the the change in emissions to be negative. This is reflected in the negative coefficient for the variables describing the fraction of CEPA-regulated and PSL-regulated outputs across the OLS and spatial regressions for all the emissions variables under consideration. The effect is negative and highly significant throughout.

The number of employees in a facility is taken as a proxy for the scale of operation so we expect the effect on the emission variables to be positive. More employees in a facility reflect a bigger

Table 3.7: OLS and Spatial Regression Models for Health-Indexed Total Emissions

Variable	Emission Levels			Emission Differences[†]		
	OLS (1)	$\mathbf{W_{GEO}}$ (2)	$\mathbf{W_{SIC}}$ (3)	OLS (4)	$\mathbf{W_{GEO}}$ (5)	$\mathbf{W_{SIC}}$ (6)
Intercept	17.586^a	16.695^a	0.951	-0.111	-0.111	-0.070
	(0.899)	(0.959)	(4.346)	(0.040)	(0.213)	(0.212)
Fraction of CEPA-regulated output	-2.625^a	-2.614^a	-2.752^a	-4.495^a	-4.495^a	-4.486^a
	(0.200)	(0.199)	(0.156)	(0.228)	(0.228)	(0.227)
Fraction of PSL-regulated output	-7.534^a	-7.515^a	-7.510^a	-6.377^a	-6.375^a	-6.334^a
	(0.938)	(0.928)	(0.913)	(0.600)	(0.597)	(0.593)
Log of Employees	0.976^a	0.973^a	0.903^a	0.282	0.284	0.294
	(0.076)	(0.075)	(0.057)	(0.223)	(0.223)	(0.221)
Log of Population (1990)	-0.209^a	-0.198^a	-0.225^a	-0.440	-0.443	-0.370
	(0.047)	(0.048)	(0.041)	(0.460)	(0.515)	(0.511)
ρ		0.044^a	0.903^a		0.012^a	0.781^a
		(0.003)	(0.222)		(0.0003)	(0.139)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
SIC dummies	Yes	Yes	No			
Adjusted R^2	0.370	0.370	0.289	0.240	0.240	0.243
Observations	1641	1641	1641	1516	1516	1516
Log-Likelihood		-3664	-3701		-1769	-1761
Spatial Multiplier, $1/(1-\rho)$		1.046	10.309		1.012	4.566

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (Health-Indexed Total Emissions). Standard errors are in parentheses.
Specifications $\mathbf{W_{GEO}}$ and $\mathbf{W_{SIC}}$ are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-2}$ and $w_{ij} = e^{-2*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (4), (5) and (6) should be interpreted as being differences.

operating scale and therefore, more emissions. The results show that this holds in all specifications with the elasticity being close to or greater than one in the level of emissions. Changes in the number of employees also have the same effect on changes in emission as shown by the positive coefficient in columns (4), (5) and (6) in the regression results tables. This means that if the scale, as measured by the number of employees, increases the emission also increases. However, the effect is not statistically significant when the dependent variables are the health-indexed emission variables.

The effect of population has the expected negative effect on the emission of a facility. This effect is also significant across all the specifications and emission variables. A higher population surrounding the polluting facility will have a greater environmental exposure while we can also expect the presence of a strong consumer pressure group in more populated areas. This result is similar to findings in related literature. We would expect changes in population density to have a positive effect on pollution abatement activities or, in other words, a negative effect effect on changes in a facility's emission. My results indicate that this effect holds in the case of health-indexed air emissions but is of the opposite sign for CAC emissions and health-indexed total emissions. In almost all cases however, the effect is statistically insignificant.

After having analysed the existence and strength of spillovers in pollution levels as well as abatement as shown by the positive and significant spatial lag parameter ρ we now turn to interpreting the spatial lag model. The effect of a change in any of the explanatory variables on the change in emissions variable at a particular facility is the sum of the direct impact as well as the induced impact and is referred to as the *spatial multiplier*. As shown in Kim et al. (2003), the spatial multiplier is expressed as $1/(1-\rho)$ if there were a unit change in every location. This means that a change in any of the explanatory variables in neighbouring facilities will have an effect on the emissions of facility i. But how much will the effect be? To find that out the elasticity of the emissions (evaluated at the mean) from a small change in the fraction of the regulated output we use

$$\varepsilon_{x_k} = \frac{\beta_k}{(1-\rho)}\bar{x}_k$$

where $\bar{x}_k$ is the mean value of x_k. The elasticity of the emissions from a small change in the neighbouring population or employees is

$$\varepsilon_{x_k} = \frac{\beta_k}{(1-\rho)}$$

For example, the elasticity of CAC emission levels from a small change in the fraction of CEPA-regulated output in column (3) of Table 3.5 is 3.535 while it is 0.273 and 2.125 for changes in population and employees respectively. If we compare these elasticity values with those obtained from the OLS regression we can see that they are significantly higher. We can, therefore, conclude that spatial dependence has a significant effect on the emissions of facilities. The elasticities for all

Table 3.8: Elasticity of Emission Variables

Variable	CAC		HI Air		HI Total	
	$\mathbf{W_{GEO}}$ (1)	$\mathbf{W_{SIC}}$ (2)	$\mathbf{W_{GEO}}$ (3)	$\mathbf{W_{SIC}}$ (4)	$\mathbf{W_{GEO}}$ (5)	$\mathbf{W_{SIC}}$ (6)
Share of CEPA-regulated output	-1.107	-3.527	-1.191	-1.728	-1.869	-3.209
Share of PSL-regulated output			-0.063	-0.097	-0.100	-0.178
Log of Employees	1.085	4.663	1.089	0.712	1.018	9.309
Log of Population	-0.179	-0.815	-0.242	-0.176	-0.207	-2.320

Note: The weight matrices $\mathbf{W_{GEO}}$ and $\mathbf{W_{SIC}}$ have $w_{ij} = (\text{geographical distance}_{ij})^{-2}$ and $w_{ij} = e^{-2*(\text{SIC distance})_{ij}}$ respectively as elements.

the significant variables are calculated in Table 3.8.

3.4.2 Extension of Standard Spatial Models

Results for the modified SAR model with two weight matrices, Eq. (3.3), are presented in Table 3.9. There are several observations to be made from comparing results of this specification with the simple OLS and the standard SAR models. Firstly, the SIC distance parameter estimates ρ_{SIC} for all the emission variables, except for difference health-indexed air emission, is positive and significant. The geographical distance parameter estimates ρ_{GEO}, while positive throughout, are not always significant. This differs from the simple SAR model in which it was positive and significant for all the emission variables. We can, therefore, conclude that the SIC industry distance may capture the spatial dependencies in pollution better than simply the geographical distance and this effect persists even after including both those spatial dependencies in the modified SAR model. Most of the ρ_{SIC} estimates are significant at the 99% level which shows that this specification is superior to ordinary least squares. Secondly, the variation in the dependent variable is explained to almost the same extent by both the OLS models and the modified spatial models and for both emission levels and emission differences.

These results show that there is a much stronger spatial dependence that arises from similar industrial facilities as compared to the spatial dependence that may arise from how far one facility is, geographically, with respect to its neighbours. Facilities in similar industries would tend to have

Table 3.9: Spatial Regression Models with Two Weight Matrices

Variable	CAC Air		HI Air		HI Total	
	Level (1)	**Diff.**† (2)	**Level** (3)	**Diff.**† (4)	**Level** (5)	**Diff.**† (6)
Intercept	1.047^a	0.101	3.813^a	0.025	0.516	-0.071
	(0.420)	(0.066)	(0.875)	(0.183)	(0.798)	(0.212)
Fraction of CEPA-regulated output	-1.454^a	-2.109^a	-2.467^a	-3.948^a	-2.752^a	-4.486^a
	(0.150)	(0.112)	(0.205)	(0.194)	(0.180)	(0.227)
Fraction of PSL-regulated output			-5.122^a	-5.465^a	-7.516^a	-6.334^a
			(1.07)	(0.526)	(0.934)	(0.593)
Log of Employees	0.854^a	0.526^a	0.980^a	0.377^b	0.905^a	0.296
	(0.039)	(0.073)	(0.076)	(0.191)	(0.067)	(0.221)
Log of Population (1990)	-0.138^a	0.224	-0.236^a	-0.716	-0.211^c	-0.375
	(0.023)	(0.162)	(0.048)	(0.457)	(0.044)	(0.511)
ρ_{GEO}	0.092^a	-0.002	0.026	0.0001	0.054^b	0.010
	(0.023)	(0.027)	(0.029)	(0.028)	(0.026)	(0.027)
ρ_{SIC}	0.780^a	0.478^b	0.710^a	-0.254	0.866^a	0.756^a
	(0.060)	(0.236)	(0.113)	(0.375)	(0.052)	(0.145)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.398	0.171	0.280	0.261	0.354	0.250
Observations	2150	2003	1426	1305	1641	1516
Log-Likelihood	-9804	-5846	-6885	-4546	-7997	-5672

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (Emissions variable). Standard errors are in parentheses.
†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (2), (4) and (6) should be interpreted as being differences.

similar emissions due to technological similarities from using similar processes. The fact that there are positive spatial autoregressive parameters ρ_{GEO} and ρ_{SIC} suggests that changes in emissions by a particular facility is, on average, being positively influenced by its neighbours, in particular, the "SIC industry" neighbours. So, for example, there is a reduction in the emissions of facility i when facility j in a "close enough" industry code also reduces its emissions. This, however, goes the other way as well. A positive spatial dependence implies that an increase in the emissions of facility i when the emissions of facility j, in a "close enough" industry code, increase.

3.5 Discussion of Results

The results in the previous section indicate the presence of strong and positive spatial dependence in pollution emissions. While this holds for both emission levels as well as emission differences, the latter is a more robust result because of the econometric superiority of using differences over levels. Even after accounting for facility-specific and location-specific factors we observe a strong spatial dependence.

The consistent theme in the results is that spillovers are more localized when geographic distance is used. The spillovers are more global in scope when the industry distance metric is considered. We can conclude this from analysing the magnitude of the spatial autoregressive parameter ρ which is larger for ρ_{SIC} than it is for ρ_{GEO} when we use both the simple spatial autoregressive regressive specification and the extended SAR model where both ρ_{SIC} and ρ_{GEO} are estimated simultaneously.

Griliches (1979) considered the issue of spillovers and posited various hypotheses for the reasons that spillovers might exist, specifically in R&D. They may be the result of horizontal, technological or vertical spillovers.[32] However, he did not consider the importance of geography. The importance of physical proximity has been recognized by recent researchers and is one of the cornerstones of spatial econometrics.

My results indicate that while physical proximity between facilities is important, the effect is overshadowed by the technological and horizontal spillovers that I capture using the industry metric. The industry metric depends on the SIC code of facilities and it captures the spillovers between firms that produce for the same market as well as firms that may be conducting similar research. Technological similarities between two firms in the same SIC code should be much higher than that of two firms that belong to different sectors within the manufacturing industry. These technological spillovers maintain their significance when I consider emission changes. This points to similar environmental performance between firms in the same sector and some form of peer effect. This effect goes beyond the borders of Canadian provinces and, hence, against some of the findings in the recent literature on spatial effects in environmental performance.

[32] Horizontal spillovers exist between firms in the same product market. Technological spillovers result from firms conducting similar research. Vertical spillovers exist between firms that are suppliers or retailers.

While geographical proximity cannot be discounted in my results, its importance is substantially weaker and corroborates recent findings on spatial dependence in environmental performance. Gray and Shadbegian (2007) find the environmental performance to be weakly spatially dependent when they use a geographic measure. Geographic distance could be a measure of regulatory threat in the sense that facilities that are closer to each other might be more affected by regulatory intervention if their emissions are high. Antweiler (2003) finds that while this threat exists it is very small in magnitude. There might be several reasons behind spatial dependence caused by geographical proximity. Facilities in the same region may have a similar environmental performance due to the presence of "demonstration effects" which is caused by facilities to be cleaner under peer pressure from other cleaner firms. The positive spatial autoregressive parameter ρ_{GEO} indicates that there is a possibility of the existence of "hot spots" where dirtier firms agglomerate. This is important in terms of the effect on potential policy. Governments have looked at ways to induce emission reductions, especially through the avenue of regulatory threat (Antweiler, 2003). The reasons behind this are to reduce costs of implementing new regulations and monitoring emissions. A positive spatial autoregressive parameter in the case of the SIC distance matrix indicates that firms in similar industries tend to have a similar environmental performance and there can be a greater focus by policy makers to target a particular industry rather than spread their resources on a wide range of industries.

3.6 Conclusion

In this essay I have used the spatial lag model and its extension to capture the spatial dependency of pollution emission levels and pollution emission changes between neighbouring facilities. Pollution emission changes are measured by taking the difference in emissions of Criteria Air Contaminants, health-indexed air emissions and health-indexed total emissions. I have weighted emissions with their toxicity because not all substances have the same impact on human health. The emissions data are from a comprehensive set of manufacturing plants located in Canada. Results show that spatial dependence does exist in the emissions of manufacturing plants and is positive indicating that emission activities by neighbouring plants are, on average, similar. Using differences in emissions accounts for plant-specific and firm-specific effects. It also ensures that province and industry-specific factors are accounted for. Taking differences also accounts for the endogeneity that may exist in the location of facilities. This is an improvement over the existing literature when looking for spillovers in pollution emitted by manufacturing facilities.

I have also used the estimates from the spatial regressions to construct spatial multipliers to interpret the implications of the spatial lag model. I show that the results are much stronger when we incorporate spatial effects compared to non-spatial models. However, the strength of the spatial dependence, as measured by the spatial dependence parameter ρ, is much stronger when we consider emission levels as compared to emission differences. Since studying emission differences is econometrically superior to looking at just emission levels we can conclude that spatial dependencies in pollution abatement, even though it does exist, may not be very strong when we consider geographical distance in the spatial weight matrix but appears to be much stronger when the SIC industry spatial weight matrix is used. This shows quite clearly that using only geographical distances for analysing spillovers in a setting where individual facilities are the units of observation may be a very simplistic and insufficient way to capture linkages.

Chapter 4

Playing Dirty or Going Clean? Lobbying, Abatement and Firm Heterogeneity

4.1 Introduction

Political lobbying is an integral part of the political scene. For example, in the US, campaign contributions for candidates running for elections sees millions of dollars being spent, especially during the Presidential race. Apart from these contributions, firms and other organizations hire lobbying firms in Washington, DC to lobby the government on various issues, including the environment and natural resources. Annual lobbying on energy and natural resources issues have been steadily increasing over the years and reached a high of over \$400 million in 2009.[33] While the amounts spent on specific issues are, to the best of my knowledge, not currently available we may assume that the lobbying amount was spent on gaining a favourable environmental policy and lobby against environmentalists. In contrast, there is also some evidence presented by Maxwell et al. (2000) that shows a sharp reduction in the amount of toxic emissions in seven main industries in the United States over the period 1988-1992 while the dollar value of shipments has increased. These are legal emissions and the reduction cannot be attributed to government regulations. This points to a role of corporate environmentalism that has become more prominent as environmental issues are being thrust more into the limelight. The most often-cited example in the literature on corporate environmentalism is the one taken up by 3M. 3M set up the Pollution Prevention Pays

[33] Center for Responsive Politics, http://www.opensecrets.org/industries/indus.php?ind=E

(3P) program in 1975 and the first year of results from 19 projects led to a reduction of 73,000 tonnes of air emissions and 2,800 tonnes of sludge.[34]

These observations form the motivation behind this essay. There is considerable evidence that polluting firms lobby the government a lot. Most of the lobbying effort goes towards stopping new regulations coming into place but sometimes companies can gain a competitive advantage by lobbying for *stricter* regulations. A case in point is that of DuPont which, after having forestalling CFC (Choloroﬂuorocarbon) regulation, changed its strategy and embraced the Montreal Protocol because it had discovered feasible alternatives to CFCs. In this chapter, I will consider lobbying *against* regulation. But there is also some evidence that some polluting firms have taken up corporate environmentalism. Are we able to make predictions about the lobbying or abatement decision of a firm by using some basic characteristics of the firm? I use three sources of firm heterogeneity in a set-up that includes two non-cooperative firms in the analysis. The three sources of heterogeneity are the marginal cost of production, the (unabated) emission intensity and their marginal cost of abatement. Using this simple model I can make some testable predictions about the decision of a firm to lobby or abate or do both. There are many possible combinations using the three sources of heterogeneity (see Table 4.1) but I will focus on the ones that are most interesting. The results of all the possible outcomes are also presented in Table 4.2 and Table 4.3.

There is a lot of anecdotal evidence of industry lobbying influencing environmental regulations and there have been studies such as Ando (1999) and Cropper et al. (1992) that have found such evidence in government regulatory agencies. While it may seem fairly obvious to see why firms may want to lobby there are various reasons for firms to decide on voluntarily abating their emissions. Firms might reduce emissions as purely a cost-saving measure. For example, in 2008, 3P prevented more than 122 million pounds of pollution and saved nearly $91 million.[35] The growth of green consumerism has also been cited as a reason for the environmental consciousness of firms. Arora and Cason (1996) and Khanna and Damon (1999) find evidence of firm participation in the 33/50 program being influenced by the amount of contact their final goods have with consumers. There may also be pressure from investors, lobby groups, residents in the neighbourhood and employees

[34] http://solutions.3m.com/wps/portal/3M/en_US/global/sustainability/s/milestones/

[35] 3M's 3P, website accessed 20$^{\text{th}}$ August, 2009.

who may all be affected by the pollution emitted by facilities. Evidence exists of investors having used the Toxics Release Inventory (TRI) data in the US to pressurize firms to reduce emissions (Hamilton, 1995; Konar and Cohen, 1997; Khanna et al., 1998). The effect of regulatory pressure on firms' emissions has also been analysed by Khanna and Damon (1999), Videras and Alberini (2000) and Antweiler (2003).

The results are obtained using a simple model with only two firms. There are several sources of firm-level heterogeneity and the various combinations of these characteristics contribute to the richness of the model. The firms behave noncooperatively and there is perfect and complete information. One crucial assumption I make throughout this analysis is the constancy of output. Once the firms make an output decision based on their marginal cost structure it cannot be modified. The firms cannot, therefore, make adjustments to their costs by changing the scale of their operations. The reason for this assumption is that firms usually find it difficult to change the scale of their operation quickly. Therefore, I assume that the only way a firm can change its emissions is through achieving the emissions standard. This, as well as lobbying, has no impact on the output produced by the firm. The main feature of the model is the lobbying and abatement choice of the firms that depend on the firm-level heterogeneity, specifically, which firm will lobby and which firm will not or which firm will abate and which firm will not.

The role of the regulator is to take into account the lobbying revenue and damage from pollution to set an environmental policy. The instrument of choice for the regulator is an emission intensity standard. While a tax is *de rigueur* in a political economy framework it is not very realistic in environmental policymaking. There is enough anecdotal evidence to suggest that governments are not very keen on introducing a tax since they tend to be very unpopular with those affected. Therefore, it is much more realistic to use a standard instead of a tax. While tariffs and taxes are quite common in the trade literature because of their prevalence in the real world, environmental taxes are not as visible. However, this has changed in recent years and some governments, especially at the provincial level, have started to introduce "green" taxes.

The main feature of the model is that only one firm will end up lobbying the regulator. So the other firm is free-riding on the lobbying activity of the first firm. Another feature is that while both firms may end up abating, for the firm that lobbies, lobbying and abatement become complementary activities and not substitutes. This arises due to the static nature of the model. For the firm that does not lobby, we can think of them abating more than the other firm and the other firm abating less but being required to compensate the regulator for abating less.

The primary contribution of this essay is that it uses firm-level characteristics to make predictions about the lobbying and abatement decision. The results are driven by cost considerations with firms choosing abatement over lobbying if the effective marginal abatement cost is lower than a threshold value. The effective marginal abatement cost is the marginal abatement cost as a function of the output and a marginal abatement cost factor.

The rest of the essay is as follows. I set up the model in the next section. Section 4.3 looks at lobbying and abatement decisions under various combinations of firm heterogeneity and makes predictions about the lobbying and abatement choices faced by each individual firm while Section 4.4 concludes.

4.2 The Model

The set-up of the model is quite simple. There are three agents, viz. two firms (indexed by $i = 1, 2$) and a regulator. The firms behave non-cooperatively. There is no informational asymmetry and the firms have perfect and complete information. Heterogeneity in the firms is modelled using three firm-level characteristics. The sources of firm heterogeneity are emission intensity ($\theta_i, i = 1, 2$), marginal cost ($c_i, i = 1, 2$) and a cost factor of abatement ($\alpha_i, i = 1, 2$). There are various ways in which the two firms could be heterogeneous. They can be different with respect to just one out of the three, two out of the three or in all characteristics. Table 4.1 provides a list of all these possible outcomes.

To begin with, I make certain assumptions about the characteristics that determine firm heterogeneity and relax some of these assumptions later. The firms have different marginal costs and I assume that firm 1 has a lower marginal cost than firm 2.

Assumption 1 *Firm 1 has a lower marginal cost than firm 2, i.e.* $c_1 < c_2$.

Table 4.1: Possible outcomes of Firm Heterogeneity

Heterogeneity in one characteristic	Heterogeneity in two characteristics	Heterogeneity in three characteristics
$c_1 = c_2$, $\theta_1 = \theta_2$, $\alpha_1 < \alpha_2$	$c_1 = c_2$, $\theta_1 < \theta_2$, $\alpha_1 < \alpha_2$	$c_1 < c_2$, $\theta_1 < \theta_2$, $\alpha_1 < \alpha_2$
$c_1 = c_2$, $\theta_1 < \theta_2$, $\alpha_1 = \alpha_2$	$c_1 = c_2$, $\theta_1 < \theta_2$, $\alpha_1 > \alpha_2$	$c_1 < c_2$, $\theta_1 < \theta_2$, $\alpha_1 > \alpha_2$
$c_1 < c_2$, $\theta_1 = \theta_2$, $\alpha_1 = \alpha_2$	$c_1 < c_2$, $\theta_1 = \theta_2$, $\alpha_1 < \alpha_2$	$c_1 < c_2$, $\theta_1 > \theta_2$, $\alpha_1 < \alpha_2$
	$c_1 < c_2$, $\theta_1 = \theta_2$, $\alpha_1 > \alpha_2$	$c_1 < c_2$, $\theta_1 > \theta_2$, $\alpha_1 > \alpha_2$
	$c_1 < c_2$, $\theta_1 < \theta_2$, $\alpha_1 = \alpha_2$	
	$c_1 < c_2$, $\theta_1 > \theta_2$, $\alpha_1 = \alpha_2$	

I also assume that one firm has a higher emission intensity than the other. Emission intensity is denoted by θ and represents the amount of unabated pollution emitted from producing one unit of output. The firm with a higher θ can, therefore, be referred to as the "dirty" firm while the firm with a lower θ can be called "clean". I assume that firm 1 is the clean firm and has an emission intensity θ_1 while firm 2 is the dirty firm and has an emission intensity θ_2. By definition, therefore, $\theta_1 < \theta_2$.

Assumption 2 *Firm 1 has a lower emission intensity than firm 2, i.e.* $\theta_1 < \theta_2$.

The above assumption means that the firm with the higher marginal cost is assumed to have a higher emission intensity. Marginal costs are a reflection of the productivity of a firm and it is reasonable to expect that a less productive firm also has a higher θ. Productivity and emission intensity are, therefore, negatively correlated or, in other words, marginal cost and emission intensity are positively correlated. This assumption will be relaxed later.

There are further costs, namely, lobbying or abatement costs or both. A firm can lobby or abate or do both. If it decides to lobby it incurs the lobbying cost. It incurs the abatement cost if it has to abate. I refer to abatement cost here as the cost incurred to meet a standard stipulated by a regulator. The profit function of firm i is given by:

$$\pi_i = (p - c_i)q_i - \begin{cases} L_i & \text{if only lobby,} \\ L_i + \alpha_i\left(\theta_i - \Theta\right)q_i & \text{if lobby and abate,} \\ \alpha\left(\theta_i - \Theta\right)q_i & \text{if only abate,} \end{cases} \tag{4.1}$$

$$L_i \geq 0,$$

where p is the market price, c_i is the marginal cost, L_i is the lobbying expense, α_i is a cost factor associated with abatement, Θ is the emission intensity standard that has been decided upon by the regulator and q_i is the output of firm i. The lobbying expense is assumed to be a fixed dollar amount and is non-negative, i.e. $L_i \geq 0$. I assume, for now, that the cost factor of abatement α_i is the same for both firms, i.e. $\alpha_1 = \alpha_2$.

Assumption 3 *The cost factor of abatement α_i is the same for both firms.*

Demand for the product is linear and the firms engage in a Cournot duopoly game to decide on the output. However, I assume that the abatement cost, if a firm has to abate, does not enter the output decision. I make a further simplification and assume that a firm does not change its output once it plays the Cournot output game. While the model is not built in a multi-stage game framework it may be convenient to think of the output decision being made at Stage 0. Lobbying and abatement decisions occur in Stage 1. The decisions and solution in Stage 1 have no bearing on the outcome in Stage 0 which precludes the need to solve the game by backward induction.

Assumption 4 *Neither firm is able to change its output decision once it has been made.*

Is the assumption to fix a firm's output restrictive? No. It is often difficult to change the scale of a plant's production quickly. So it is quite reasonable to assume that a firm is unable to change the quantity it produces in response to a change in its cost structure. Given a linear demand structure, $p = a - b(q_1 + q_2)$, the profit maximizing output of firm i is obtained from the standard Cournot model and is $q_i^* = \dfrac{a - c_i}{3b}$. Since the marginal costs are not symmetric the firm with a higher marginal cost, firm 2 in this case, will have a lower output than firm 1. It is also very straightforward to show that firm 1 will have a higher profit than firm 2. What about their respective unabated emissions? While firm 1 has a lower emission intensity than firm 2 it also produces more output than firm 2. So it is not obvious which firm has greater unabated emission. It can be shown that if the difference in marginal costs is sufficiently small firm 2 will have a higher unabated emission than firm 1. I assume, for simplicity, that this indeed is the case so that firm 2 has a higher unabated emission than firm 1.

Assumption 5 *Firm 1 has a lower unabated emission than firm 2, i.e.* $\theta_1 q_1 < \theta_2 q_2$.

I will, from now, concentrate on the cost part of the profit function that includes the lobbying and abatement expenditure since $(p - c_i)q_i$ will remain unchanged for both firms. Before analysing the behaviour of firms in terms of their lobbying and abatement activities I need to introduce the regulator and discuss its role.

The objective of the regulator is to consider the lobbying activities of the firms and balance it against the damages caused by pollution to decide on the appropriate regulation. The stringency of regulation depends on how the lobbying activities influence the regulator. The regulator sets an emission intensity standard Θ that is applicable to both firms. The possibility of a firm garnering a favour for itself by influencing the regulator independently is ignored. So, even if one firm is successful in enforcing a weak regulation it will apply to the other firm too. The regulator's welfare function is determined by the lobbying amount it receives from the polluting firms and the damage the pollution causes in its area. So the regulator has an objective function[36] given by:

$$G = \lambda(L_1 + L_2) - (1 - \lambda) \left[\min\{\theta_1, \Theta\} q_1 + \min\{\theta_2, \Theta\} q_2\right]^2, \tag{4.2}$$

where λ is the weight assigned to lobbying and $(1 - \lambda)$ is the weight assigned to the damages from pollution. The range of λ is $[0, 1]$. L_1 and L_2 are the lobbying expenditures of firms 1 and 2 respectively. Θ is the emission intensity standard, applicable to both firms, set by the regulator. The outputs of the two firms are, respectively, q_1 and q_2. The term in square brackets denotes the damage caused by pollution. It is a quadratic expression to signify that the effect of the damage

[36]The pollution damage can be transformed into monetary form by normalizing the "price" of pollution to one.

becomes progressively worse with higher emissions. The pollution from firm i is the product of emission intensity and output of firm i. The emission intensity is the lower of the emission intensity chosen by the regulator Θ and the exogenously given original emission intensity of firm i. Θ is the ex-post emission intensity only if the regulator chooses the standard such that it is below the firm's original θ_i. The weights assigned to lobbying and pollution will determine how the regulator sets Θ. If $\lambda = 1$ the regulator only cares about lobbying revenue and when $\lambda = 0$ the concern for the regulator is only the damage from pollution. We may also think of λ as a measure of lobbying effectiveness. If λ is less than 1 the firms will not be able to lobby as effectively as when it is closer to 1. It is clear from (4.2) that lobbying increases the regulator's welfare while the damage from pollution reduces it.

The objective of the regulator will be to balance the cost from pollution and benefit from lobbying revenue by choosing an emission intensity standard so that the welfare is maximized. However, for the purposes of this essay I will assume that the regulator is weak and has a minimum amount of welfare it accepts on society's behalf. Any further damages from pollution can be compensated by the lobbying amount. This will lead to the situation where the welfare will remain at that minimum level and the polluting firms will lobby the regulator to relax the standard in return for more political contribution. Therefore, this model differs from the standard Grossman and Helpman (1994) political economy model where the policymaker can capture rents from tariff formation. The implicit assumption of a weak government, while presumably strong, is quite realistic especially with regard to environmental policy. Environmental policy is still not a priority for governments that believe other issue require more immediate intervention. Therefore, it is realistic to believe that regulators accept damage from pollution as long as the welfare of society is not seriously compromised. A recent book by Pielke Jr. (2010) illustrates the unsuccessful nature of environmental policies with respect to reducing carbon dioxide emissions. He refers to this failure as the "iron law" of climate politics: "When policies focused on economic growth confront policies focused on emissions reduction, it is economic growth that will win out every time."

Let us assume, therefore, that the regulator has a lower limit to the damage that pollution can cause if it were to ignore lobbying. This implies that the regulator has an acceptable limit to the damage that society can accept from pollution. If the regulator were to set Θ in the absence of lobbying such that damages would be minimized then that optimal value of Θ would be zero. I ignore that possibility and assume that there is a minimum welfare loss that the regulator can accept. Denote that limit by $\bar{G}$ which, by definition, is negative.[37]

Assumption 6 *The regulator fixes a minimum welfare amount at $\bar{G}$ which sets the limit to how much damage the society is willing to accept in the absence of any lobbying. The value of $\bar{G}$ is negative.*

If the regulator ignores lobbying by setting λ equal to 0, it will be able to find a value of the emission intensity standard Θ such that $\bar{G}$ is attained. With the presence of lobbying, that value of Θ can be weakened. While this would lead to higher damages from the weaker standard, the loss would be compensated by the increased revenue received by the regulator from lobbying. Assume, for now, that the emission intensity standard is binding on both firms and that the regulator assigns positive weights to both lobbying and pollution damage. We can write the modified objective function as:

$$\bar{G} \leq \lambda(L) - (1-\lambda)\left[\Theta q_1 + \Theta q_2\right]^2, \tag{4.3}$$

where L is the total lobbying the regulator receives. This weak inequality will hold with equality since there is no incentive for firms to lobby more than necessary. We can then find the value of Θ such that the difference between lobbying revenue and pollution damage is equal to $\bar{G}$ by equating the two sides in (4.3) to get:

$$\Theta^* = \sqrt{\frac{\lambda L - \bar{G}}{(1-\lambda)Q^2}}, \tag{4.4}$$

where $Q = q_1 + q_2$. Recall that $\bar{G} < 0$ so the numerator is positive. We can see from this expression that the emission intensity standard Θ^* increases when lobbying amount L increases. It also increases when the regulator assigns more weight λ to lobbying. In other words, increased lobbying and more weight to lobbying by the regulator weakens the emission intensity standard. These observations lead to the following proposition.

[37] Assume that the regulator ignores lobbying. Then the welfare depends on the pollution damage which is negative. The regulator, therefore, has a minimum welfare amount in mind below which it is unwilling to go.

Proposition 1 *The emission intensity standard set by a regulator is weakened by an increase in lobbying amount as well as by an increase in the weight assigned to lobbying. The standard is made stronger if the government reduces the minimum welfare loss $\bar{G}$.*

To find out the effect that each firm's lobbying has on Θ^* we differentiate (4.4) with respect to firm 1's lobbying L_1 and firm 2's lobbying L_2. The expressions are identical:

$$\frac{\partial \Theta^*}{\partial L_1} = \frac{\partial \Theta^*}{\partial L_2} = \frac{\beta}{2\Theta^*} > 0, \tag{4.5}$$

where $\beta = \lambda/(1-\lambda)$. The effect of lobbying on the standard Θ^* is positive, i.e. it becomes weaker and more favourable to firms. The reason that the effect of lobbying by both firms on the regulator's policy instrument is the same is because the source of the contribution is irrelevant to the regulator. It treats a dollar equally regardless of whether it came from firm 1 or firm 2.

The next section analyses the lobbying and abatement choice of each of the two firms. In the event that the two firms have unequal unabated emission intensities the emission standard set by the regulator could be strict enough to be lower than the emission intensities of both firms. It would then be binding for both firms. However, the emission standard could be not binding for the firm with the lower θ and also not binding for either firm. I will, first, discuss the situation where the emission standard is binding for both firms and then discuss, briefly, the other two cases.

4.3 Lobbying and Abatement

4.3.1 Binding Emission Standard

Now that we have found out the optimal Θ and the effect that each firm's lobbying has on the regulator's emission intensity standard let us turn to the two firms and look at their lobbying contribution choice. Can we say anything about which firm will lobby and which firm will not? For that we need to return to the profit function (4.1). The FOC for profit maximization with respect to lobbying expenditure L_i for firm i is:

$$-1+\alpha_i q_i \frac{\partial \Theta^*}{\partial L_i} \leq 0 \tag{4.6}$$

$L_i \geq 0$ with complementary slackness.

We can rearrange (4.6) and use (4.5) to get:

$$\alpha_i q_i \leq \frac{2\Theta^*}{\beta} \tag{4.7}$$

$L_i \geq 0$ with complementary slackness.

The left-hand side of (4.7) is the marginal abatement cost that is also a function of the firm's output. A firm with a high output will also have a high abatement cost since the output in my model is assumed to be fixed. A high abatement cost factor α_i will also lead to a high abatement cost. The condition (4.7) is a convenient way to look at the firm's decision problem as to whether it should lobby or abate. If the abatement cost is lower than the $\frac{2\Theta^*}{\beta}$ threshold it will be more cost-effective to abate while it should put in at least some effort in lobbying when the condition (4.7) holds with equality.

Since, by the set-up of the model, $q_1 > q_2$ and because $\frac{\partial \Theta^*}{\partial L_1} = \frac{\partial \Theta^*}{\partial L_2}$, (4.7) will hold with equality for firm 1 and with a strict inequality for firm 2:

$$\alpha q_1 = \frac{2\Theta^*}{\beta}, \tag{4.8a}$$

and

$$\alpha q_2 < \frac{2\Theta^*}{\beta}, \tag{4.8b}$$

These conditions indicate that it is more cost-effective for firm 1 to lobby but not for firm 2. Therefore, $L_1 > 0$ for firm 1 and $L_2 = 0$ since we end up with a corner solution for firm 2's lobbying effort. Firm 1 will lobby and firm 2 will not lobby. What is firm 1's lobbying effort? That is obtained by substituting Θ^* from (4.4) into (4.8a):

$$L_1 = \frac{\bar{G}}{\lambda} + \beta \left(\frac{\alpha q_1}{2}\right)^2. \tag{4.9}$$

In terms of abatement activity, both firms will have to abate since the emission intensity standard, by assumption, is binding for both of them. So the total abatement cost will be $\alpha(\theta_i - \Theta^*)q_i$ for firm i. The total abatement cost for firm 2 will be more than that of firm 1 provided that $\theta_1 q_1 < \theta_2 q_2$. Otherwise, if the inequality is reversed, firm 1 will have a higher total abatement cost than firm 2. We can write these results in the next proposition.

Proposition 2 *Assuming that the emission standard is binding for both firms, the "clean" (with respect to the emission intensity) firm will lobby the regulator to weaken the emission standard while the "dirty" firm will not lobby. The total abatement cost of the "dirty" firm will be higher than that of the "clean" firm.*

The FOC conditions (4.8a) and (4.8b) and the slackness conditions are crucial for analysing the lobbying decision of firms. Using these two conditions we can predict the conditions under which a firm will lobby. These conditions will depend on the characteristics of the firm in terms of the scale of production (reflected in the amount of output produced) and various cost parameters. The firm whose FOC is not binding will not lobby while the firm whose FOC is binding and equal to zero will lobby. Using this property let us now look at the firm characteristics that will determine which firm lobbies.

There are three sources of firm heterogeneity in this model. The two firms can be different in terms of their emission intensity θ_i, the output produced q_i (caused by a difference in marginal cost c_i) and the cost factor of abatement α_i. I have initially assumed that the marginal cost of firm 1 is lower than that of firm 2. If I reverse the inequality and assume that $c_1 > c_2$ the output of firm 1 will be lower than that of firm 2. Therefore, the equality in (4.8a) will be relaxed while equality will be gained in (4.8b). The new conditions will be:

$$\alpha q_1 < \frac{2\Theta^*}{\beta}, \tag{4.10a}$$

$$\alpha q_2 = \frac{2\Theta^*}{\beta}. \tag{4.10b}$$

since $q_1 < q_2$. So firm 2 will now lobby but not firm 1. The result we get here is that bigger and dirtier firms will lobby. The lobbying amount is determined in the same way as before and is:

$$L_2 = \frac{\bar{G}}{\lambda} + \beta \left(\frac{\alpha q_2}{2}\right)^2. \tag{4.11}$$

In terms of the abatement activity, both firms will have to abate since the emission intensity standard is binding for both of them. So the total abatement cost will be $\alpha(\theta_i - \Theta^*)q_i$ for firm i. The total abatement cost for firm 2 will be more than that of firm 1 since $\theta_1 q_1 < \theta_2 q_2$. Therefore, the bigger and dirtier firm will have to lobby and abate. Reversing the assumption on marginal costs gives us the following proposition.

Proposition 3 *Assuming that the emission standard is binding for both firms, the bigger (in terms of output) and dirtier (with respect to the emission intensity) firm will lobby the regulator to weaken the emission standard while the smaller and cleaner firm will not engage in lobbying. The total abatement cost of the dirtier firm will be higher than that of the cleaner firm.*

Let us now relax the assumption that the marginal cost of abatement is the same for both firms and assume that it is lower for the dirty firm, i.e. $\alpha_1 > \alpha_2$. This can be explained by the observation that abatement is a "low-hanging fruit" for the dirtier firm. The firms are, in this case, heterogeneous in all three characteristics. If we return to the FOC conditions for the two firms we get the following conditions:

$$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}, \tag{4.12a}$$

$$\alpha_2 q_2 < \frac{2\Theta^*}{\beta}. \tag{4.12b}$$

Since $q_1 > q_2$ (because $c_1 < c_2$) and $\alpha_1 > \alpha_2$ the effective marginal abatement cost will hold with equality for firm 1 but with strict inequality for firm 2. We are then in a corner solution for firm 2 with respect to its lobbying effort and, as a result, $L_2 = 0$. In terms of abatement effort, firm 2 will have to abate more since $\theta_2 > \theta_1 > \Theta^*$ but the cost of abatement is ambiguous. Firm 1 will have a higher abatement cost compared to firm 2 if $\frac{\alpha_1 q_1}{\alpha_2 q_2} > \frac{\theta_2 - \Theta^*}{\theta_1 - \Theta^*}$ while firm 2 will have a higher total abatement cost if the inequality is reversed and both firms will have the same abatement cost when it holds with equality. This ambiguity is quite straightforward to explain. Since the marginal abatement cost of the larger firm (firm 1) is larger than that of the smaller firm (firm 2) it works against it even though the smaller firm with the lower marginal abatement cost has a larger emission intensity. Firm 1 will have a lower total abatement cost only if firm 2 has a sufficiently high emission intensity θ_2. We can write this result in the following proposition:

Proposition 4 *Assume that the emission standard is binding for both firms and the marginal abatement cost factor is negatively correlated with the emission intensity. The larger and cleaner firm will lobby while the smaller and dirtier firm will not. The total abatement cost of the dirtier firm will be higher than that of the cleaner firm only if its emission intensity is sufficiently high. Otherwise, its total abatement cost will be less (or equal).*

What about the situation when the marginal abatement cost factor and emission intensity are positively correlated so that that the larger firm (firm 1) has a lower emission intensity as well as a lower marginal abatement cost? We then have:

$$\alpha_1 q_1 \leq \frac{2\Theta^*}{\beta}, \tag{4.13a}$$

$$\alpha_2 q_2 \leq \frac{2\Theta^*}{\beta}. \tag{4.13b}$$

Since $q_1 > q_2$ and $\alpha_1 < \alpha_2$ we cannot say with certainty which FOC will hold with equality. It will depend on the $\alpha_i q_i$ term. If $\alpha_1 q_1 > \alpha_2 q_2$ then firm 1 will lobby and firm 2 will not. What can we say about their abatement expenses? Unfortunately, not much. Even if $\alpha_1 q_1 > \alpha_2 q_2$ the result is ambiguous because $\theta_1 < \theta_2$. Firm 1 will have a higher abatement cost if $\frac{\alpha_1 q_1}{\alpha_2 q_2} > \frac{\theta_2 - \Theta^*}{\theta_1 - \Theta^*}$. However, if we know that $\alpha_1 q_1 < \alpha_2 q_2$ firm 2 will have a higher abatement cost compared to firm 1 since $\frac{\alpha_1 q_1}{\alpha_2 q_2} < \frac{\theta_2 - \Theta^*}{\theta_1 - \Theta^*}$. In this case firm 1 will not lobby but firm 2 will.

Proposition 5 *Assume that the emission standard is binding for both firms and the marginal abatement cost is positively correlated with the emission intensity. The larger and cleaner firm will* *lobby while the smaller and dirtier firm will not if the marginal cost of abatement is sufficiently high for the former. Otherwise, only the smaller and dirtier firm will lobby.*

The assumption up to now has been that the larger firm has a lower emission intensity. However, it may be the case that larger firms are the ones that are comparatively dirtier. So let us now consider the situation where $c_1 < c_2$ which implies that firm 1 produces more than firm 2 and $\theta_1 > \theta_2$ so that firm 1 is dirtier too. Given these assumptions there are two possible outcomes with regard to the marginal cost of abatement. Firstly, the emission intensity and the marginal cost of abatement can be positively correlated so that the firm with the higher emission intensity also has a higher marginal cost of abatement. Secondly, if we assume that abatement is a "low-hanging fruit" for the dirtier firm we have the situation where emission intensity and marginal cost of abatement are inversely related.

Let us assume that the larger firm has a higher emission intensity and the emission intensity and marginal cost of abatement are positively correlated. We have $c_1 < c_2$, $\theta_1 > \theta_2$ and $\alpha_1 > \alpha_2$. The FOCs for lobbying can be rewritten as:

$$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}, \tag{4.14a}$$

$$\alpha_2 q_2 < \frac{2\Theta^*}{\beta}, \tag{4.14b}$$

where the effective marginal abatement cost for firm 1 holds with equality but with inequality for firm 2 because $\alpha_1 q_1 > \alpha_2 q_2$. Firm 1 will therefore lobby a strictly positive amount but firm 2 will not engage in any lobbying activity. Using our assumptions, it is easy to prove that $\alpha_1(\theta_1 - \Theta^*)q_1 > \alpha_2(\theta_2 - \Theta^*)q_2$ so firm 1 will spend more on abatement activity than firm 2.

Proposition 6 *Assume that the emission standard is binding for both firms, the larger firm is the dirtier firm and the marginal abatement cost is positively correlated with the emission intensity. The larger and dirtier firm will lobby while the smaller and cleaner firm will not. The total abatement cost of the larger and dirtier firm will also be higher than that of the smaller but cleaner firm.*

If we reverse the correlation between emission intensity and marginal cost of abatement the situation becomes less unambiguous. We now have $c_1 < c_2$, $\theta_1 > \theta_2$ and $\alpha_1 < \alpha_2$. The FOCs can be rewritten as:

$$\alpha_1 q_1 \leq \frac{2\Theta^*}{\beta}, \tag{4.15a}$$

$$\alpha_2 q_2 \leq \frac{2\Theta^*}{\beta}. \tag{4.15b}$$

This case is similar to (4.13a) and (4.13b). Since $q_1 > q_2$ and $\alpha_1 < \alpha_2$ we cannot say with certainty which firm's effective marginal abatement cost will be lower than the threshold value. It will depend on the $\alpha_i q_i$ term. If $\alpha_1 q_1 > \alpha_2 q_2$ then firm 1 will lobby and firm 2 will not. We cannot say anything with certainty about their abatement expenses. If we know that $\alpha_1 q_1 > \alpha_2 q_2$ firm 1 will have a higher abatement cost compared to firm 2 since $\alpha_1(\theta_1 - \Theta^*)q_1 > \alpha_2(\theta_2 - \Theta^*)q_2$. However, this is not certain when $\alpha_1 q_1 < \alpha_2 q_2$ because $\alpha_1(\theta_1 - \Theta^*)q_1$ could be greater than, equal to or less than $\alpha_2(\theta_2 - \Theta^*)q_2$. In this case, firm 1 will lobby but not firm 2.

Proposition 7 *Assume that the emission standard is binding for both firms, the larger firm is the dirtier firm and the marginal abatement cost is negatively correlated with the emission intensity. The larger and dirtier firm will lobby while the smaller and cleaner firm will not if the marginal cost of abatement is sufficiently high for the former. Otherwise, only the smaller and cleaner firm will lobby.*

I have assumed till now that the marginal costs for the two firms are unequal. They are, therefore, heterogeneous in terms of size. Suppose that assumption is modified and both firms have the same marginal cost, i.e. $c_1 = c_2 = c$. The output produced will then be equal for both firms, $q_1 = q_2 = q$. This assumption is very useful if we want to look at the lobbying and abatement behaviour of two firms that are of the same size. Firm 2 is the dirtier firm but has a lower marginal abatement cost so emission intensity and the marginal cost of abatement are negatively correlated. This implies that $\theta_1 < \theta_2$ and $\alpha_1 > \alpha_2$. We get the following conditions:

$$\alpha_1 q = \frac{2\Theta^*}{\beta}, \tag{4.16a}$$

$$\alpha_2 q < \frac{2\Theta^*}{\beta}. \tag{4.16b}$$

Therefore, using the same argument as in the preceding cases, firm 1 will lobby but firm 2 will not. When it comes to abatement activity firm 1 will abate $\alpha_1(\theta_1 - \Theta^*)q$ and firm 2 will abate $\alpha_2(\theta_2 - \Theta^*)q$. The difference in abatement expenditure will depend on $\alpha_1(\theta_1 - \Theta^*)$ and $\alpha_2(\theta_2 - \Theta^*)$. If $\alpha_1(\theta_1 - \Theta^*) > \alpha_2(\theta_2 - \Theta^*)$ then firm 1 will have a higher abatement expenditure than firm 2. The abatement expenditures will be reversed if $\alpha_1(\theta_1 - \Theta^*) < \alpha_2(\theta_2 - \Theta^*)$. These relations may be simplified to ratios so that firm 1 will have a higher abatement expenditure than firm 2 if $\frac{\alpha_1}{\alpha_2} > \frac{\theta_2 - \Theta^*}{\theta_1 - \Theta^*}$. Firm 1 will have a higher abatement expenditure if its marginal cost abatement is sufficiently higher than that of firm 2 compared to the ratio that they both have to reduce their emission intensities by. If, on the other hand, firm 2 has to reduce its emission intensity by a sufficiently large amount the total abatement cost it faces will exceed that of firm 1. There may also exist a situation where the two ratios are equal in which case the abatement expenditures will also be the same.

Proposition 8 *Assume that two firms are of the same size and that the emission standard is binding for both. If the emission intensity and marginal cost of abatement are negatively correlated so that the firm with a higher emission intensity has a lower marginal cost of abatement, the clean firm will lobby while the dirty firm will not. There is ambiguity in terms of their total abatement expenditures.*

The other interesting case where two firms are of the same size occurs when the emission intensity and the marginal cost of abatement are positively correlated. This is opposite to the previous discussion and therefore, in this case the firm with a higher emission intensity has a higher marginal cost of abatement. Assuming that firm 1 is still the cleaner firm we have $\theta_1 < \theta_2$ and $\alpha_1 < \alpha_2$. We can then derive the following conditions from the FOCs:

$$\alpha_1 q < \frac{2\Theta^*}{\beta}, \tag{4.17a}$$

$$\alpha_2 q = \frac{2\Theta^*}{\beta}. \tag{4.17b}$$

Table 4.2: Lobbying and Abatement when Two Firms are of Equal Size

	Heterogeneity combinations	Complementary Slackness	Lobbying	Abatement Expenditure
(1)	$\theta_1 = \theta_2$, $\alpha_1 < \alpha_2$	$\alpha_1 q < \frac{2\Theta^*}{\beta}$ $\alpha_2 q = \frac{2\Theta^*}{\beta}$	$L_1 = 0$ $L_2 > 0$	Firm 1 < Firm 2
(2)	$\theta_1 < \theta_2$, $\alpha_1 = \alpha_2$	$\alpha_1 q = \frac{2\Theta^*}{\beta}$ $\alpha_2 q = \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 > 0$	Firm 1 < Firm 2
(3)[§]	$\theta_1 < \theta_2$, $\alpha_1 < \alpha_2$	$\alpha_1 q < \frac{2\Theta^*}{\beta}$ $\alpha_2 q = \frac{2\Theta^*}{\beta}$	$L_1 = 0$ $L_2 > 0$	Firm 1 < Firm 2
(4)[§]	$\theta_1 < \theta_2$, $\alpha_1 > \alpha_2$	$\alpha_1 q = \frac{2\Theta^*}{\beta}$ $\alpha_2 q < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $\lesseqqgtr$ Firm 2

Note: [§] refers to cases that are discussed in the essay.

Therefore, the effective marginal abatement cost is lower for firm 1 than for firm 2. This implies that there is an interior solution for firm 2 in terms of lobbying and a corner solution for firm 1. Therefore, $L_2 > 0$ and $L_1 = 0$ for firm 2 and firm 1 respectively. Compared to the previous case where emission intensity and marginal cost of abatement were inversely related there is no ambiguity in terms of the total abatement expenditure. The abatement expenditure is $\alpha_1(\theta_1 - \Theta^*)q$ for firm 1 and $\alpha_2(\theta_2 - \Theta^*)q$ for firm 2. Since $\theta_1 < \theta_2$ and $\alpha_1 < \alpha_2$ we have $\alpha_1(\theta_1 - \Theta^*)q < \alpha_2(\theta_2 - \Theta^*)q$. Firm 2 has a higher abatement cost compared to firm 1. This is because firm 2 has to abate more to reach the new emission standard and also the cost of abating to that standard is higher.

Proposition 9 *Assume that two firms are of the same size and that the emission standard is binding for both. If the emission intensity and marginal cost of abatement are positively correlated so that the firm with a higher emission intensity has a higher marginal cost of abatement, the clean firm will lobby while the dirty firm will not. The dirtier firm will, unambiguously, have a higher* *total abatement cost.*

Table 4.3: Lobbying and Abatement when Firm 1 is Larger Than Firm 2

	Heterogeneity combinations	Complementary Slackness	Lobbying	Abatement Expenditure
(1)	$\theta_1 = \theta_2$, $\alpha_1 = \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $>$ Firm 2
(2)	$\theta_1 = \theta_2$, $\alpha_1 < \alpha_2$	$\alpha_1 q_1 \leq \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 \leq \frac{2\Theta^*}{\beta}$	$L_1 \geq 0$ $L_2 \geq 0$	Firm 1 $\lesseqqgtr$ Firm 2
(3)	$\theta_1 = \theta_2$, $\alpha_1 > \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $>$ Firm 2
(4)[§]	$\theta_1 < \theta_2$, $\alpha_1 = \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $\lesseqqgtr$ Firm 2
(5)	$\theta_1 > \theta_2$, $\alpha_1 = \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $>$ Firm 2
(6)	$\theta_1 < \theta_2$, $\alpha_1 < \alpha_2$	$\alpha_1 q_1 \leq \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 \leq \frac{2\Theta^*}{\beta}$	$L_1 \geq 0$ $L_2 \geq 0$	Firm 1 $\lesseqqgtr$ Firm 2
(7)[§]	$\theta_1 < \theta_2$, $\alpha_1 > \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $\lesseqqgtr$ Firm 2

Continued on Next Page...

Table 4.3 – Continued

	Heterogeneity combinations	Complementary Slackness	Lobbying	Abatement Expenditure
(8)[§]	$\theta_1 > \theta_2$, $\alpha_1 < \alpha_2$	$\alpha_1 q_1 \leq \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 \leq \frac{2\Theta^*}{\beta}$	$L_1 \geq 0$ $L_2 \geq 0$	Firm 1 $\lesseqqgtr$ Firm 2
(9)[§]	$\theta_1 > \theta_2$, $\alpha_1 > \alpha_2$	$\alpha_1 q_1 = \frac{2\Theta^*}{\beta}$ $\alpha_2 q_2 < \frac{2\Theta^*}{\beta}$	$L_1 > 0$ $L_2 = 0$	Firm 1 $\lesseqqgtr$ Firm 2

Note: [§] refers to cases that are discussed in the essay.

Using the results in Table 4.3 to illustrate the behaviour of lobbying activity is an useful exercise. Let us assume that there is a positive correlation between the (unabated) emission intensity θ and the marginal cost of abatement α which means that the dirtier firm has a higher marginal cost of abatement. Given this assumption, we can study how lobbying activity changes for the two firms when their relative size changes. If firm 1 is smaller than firm 2 we are in the situation where $c_1 > c_2$, $\theta_1 < \theta_2$ and $\alpha_1 < \alpha_2$. This is similar to Case 9 in Table 4.3.[38] Firm 1 will not lobby but firm 2 will. As the relative size of firm 1 increases and we reach the point where the two firms are equal in size firm 1 will still not lobby but firm 2 will keep lobbying. If firm 1 is larger than firm 2 both firms may or may not lobby. We see that for dirtier firms that also have a higher abatement cost it is more effective for them to lobby and abate than to just abate. Their effective marginal cost of abatement is too high which means that they need to lobby the government for a weaker standard as well as abate to meet the resulting standard.

If, on the other hand, we assume that the dirtier firm has a lower marginal cost of abatement

[38] Case 9 in Table 4.3 refers to the situation where firm 1 is larger than firm 2. But if we switch the notation for firm 1 and firm 2 we get the following conditions: $c_2 < c_1$, $\theta_2 > \theta_1$ and $\alpha_2 > \alpha_1$. It is, therefore, just a slight change in notation and the result follows.

so that the cost of abating is a low-hanging fruit, we see that as the relative size of the cleaner firm increases we will get a situation where it will be the only firm that lobbies. This occurs once it reaches and exceeds the size of the dirtier firm. This emphasizes the role that the effective marginal cost of abatement plays in determining the lobbying and abatement choice of a firm. It does not matter if a firm has a lower unabated emission intensity. If its size exceeds a limit then it will be the only firm that lobbies even though the other firm has a higher unabated emission intensity. If the effective marginal cost of abatement is sufficiently low, the dirtier firm will find abating to be more cost-effective than lobbying.

4.3.2 Binding Emission Standard for only One Firm

I now discuss the situation where the emission standard is binding for one firm but not for the other. It is quite clear that, if it *is* binding, it will be binding for the firm with the higher emission intensity.[39] In this situation Θ^* will lie above θ_1 but below θ_2. The results, in terms of lobbying, will not change because they do not depend on the new emission standard. The only difference from the situation with the emission standard binding on both firms is that there will be no abatement expenditure for firm 1 but it will be positive for firm 2. The lobbying decision as to which firm will lobby and which firm will not is given by Table 4.2 and Table 4.3.

When the two firms are of equal size. two cases strike out as being interesting. The first arises when firm 1 has a lower marginal cost of abatement. In this case firm 1 does not lobby but the dirtier firm does. The dirtier firm also has to abate because there is a point beyond which it finds abating to be more cost-effective than lobbying. We therefore have a situation in which the cleaner firm is being passive while the dirtier firm is doing both lobbying and abatement.

The second interesting case occurs when the the cleaner firm has a higher marginal abatement cost. The cleaner firm will lobby the regulator to weaken the emission standard while the dirtier firm will abate instead of lobbying. The dirtier firm is free-riding on the lobbying efforts of the cleaner firm. Abating turns out to be more expensive for the cleaner firm and so it ends up lobbying the regulator. The dirtier firm finds abating to be more cost-effective.

[39] I am ruling out the case where both firms have the same emission intensity. Also, my assumption about firm 1 being the cleaner firm still holds.

4.3.3 No Binding Emission Standard

There might also be a situation where the emission standard set by the regulator is sufficiently weak and none of the firms are bound by it. This could happen if the weight assigned by the regulator to lobbying effort by the firms is sufficiently high. In that case, we will have a situation where firms will only lobby and not find it necessary to abate and the difference in emission intensity will play no role. The lobbying effort will follow the same pattern as in Table 4.2 and Table 4.3 but we need only focus on the differences in the marginal cost of abatement α_i and the sizes of the firms because those two factors alone will determine whether a firm lobbies or not.

For two firms of equal size the lobbying decision will depend on the marginal cost of abatement. The firm with the higher value of α_i will find it more cost-effective to lobby than the other firm and, since the firms behave non-cooperatively, the other firm will free-ride and not need to lobby.

The factor that determines the lobbying choice depends crucially on the $\alpha_i q_i$ term. Since it reflects the effective cost of abatement, by taking into account how much the firm has to abate over all its production units as well as the marginal cost of abatement, the firm with the higher value will find it more cost-effective to lobby than to engage in any abatement activity.

4.4 Conclusion

In this essay I have used firm heterogeneity to look at situations under which firms will lobby or abate or do both. Starting with a simple model with two firms and using three sources of firm heterogeneity, *viz.* emission intensity, marginal cost and cost factor of abatement, I have shown that, under certain assumptions, the dirtier firm with a higher marginal cost of abatement will lobby and abate while the cleaner firm with the lower marginal cost of abatement will find it more effective to abate and not lobby. The model shows that, for small and clean firms, there is no lobbying activity when the firm size is small. As it increases, relative to the dirtier firm, there is a greater possibility of the firm engaging in lobbying activity. All these results depend crucially on the effective marginal cost of abatement which takes into account the marginal cost of abatement as well as the output of the firm. If it is sufficiently low, then the firm has no incentive to lobby the regulator. Because the firms are not symmetrical one of the two will have the incentive to lobby. Using a simple model with two firms, I have been able to make a number of predictions. This has been possible due to the sources of firm heterogeneity. The model also includes a few policy variables that enrich the model. The crucial policy variable is the emission intensity standard which is a much more widely used policy instrument than a green tax.

Chapter 5

Conclusion

In this thesis I explore three different issues in environmental economics. In the first essay my co-author, Sumeet Gulati, and I analyse the effectiveness of a particular Demand Side Management (DSM) initiative taken up by the electric utility industry. The DSM program that is of our interest is the effectiveness of cash rebates offered to customers for purchasing energy efficient ENERGY STAR appliances in the United States. This issue is of particular relevance now because of concerns that greenhouse gases (GHGs) are causing global climate change. Persuading people to switch to more efficient household appliances would lead to some reduction in the emission of GHGs because they would consume less energy. Less energy means less electricity having to be produced thus causing a reduction in the burning of fossil fuels which cause GHGs to be produced. The US generates more than 50% of its electricity from fossil fuels which means that using less electricity would cause less utilization of fossil fuels. Reducing electricity consumption also leads to a reduction in the need to build new power plants, leads to better grid reliability, better pollution control by utilities and savings to consumers. Utility companies, therefore, started on an aggressive marketing of energy efficient household appliances under the ENERGY STAR label. They did this by providing rebates to consumers if they bought these appliances. The average ENERGY STAR model is much more expensive than a standard model so customers were offered these incentives. Being energy-efficient, these appliances also tend to have a lower operational cost compared to a standard model.

While there have been numerous reports on the penetration of these efficient appliances in the household and corporate sector there has not been any study done, to the best of our knowledge, on how effective these rebates were in persuading customers to purchase the ENERGY STAR models. We have analysed the effectiveness of the rebates program by using data from all the 50 US states over a period of 6 years between 2001 and 2006 (both years inclusive). We have used various data sources to construct the dataset. The two main sources of data are a detailed dataset of all utility rebates offered by utility companies and a dataset that provide details on the share of Energy Star appliances sold in each state by quarter. The appliances we have considered are clothes washers, dishwashers and refrigerators. We have also used some demographic variables that were obtained from the Current Population Survey (CPS) and the US Bureau of Economic Analysis and electricity prices from the US Department of Energy. To estimate the impact of these incentives we use the variation in timing and size of the utility rebates across the US states. Our results show that a dollar increase in the rebate leads to a 0.3% increase in the share of Energy Star-qualified clothes washers while the effect of rebates is not significant for dishwashers and refrigerators. We then use these estimates along with information on the average energy saved by using an Energy Star appliance relative to a non-Energy Star appliance to provide a rough estimate on the cost per tonne of carbon saved by the rebate program. The cost of saving a tonne of carbon through the clothes washer rebate program is calculated to be approximately US$171. The corresponding cost of a megawatt hour saved (approximately US$35), is lower than the estimated cost of building and operating an additional power plant and the average on-peak spot price between 2001 and 2006. We conclude that the Energy Star clothes washers rebate programs are a cost-effective way for utilities to reduce energy demand.

An important feature of our research is the use of utility-level rebate programs that have been aggregated up to the state level. This allows us to capture the effect of these DSM programs on the market share of energy-efficient Energy Star appliances. However, this is also a limitation of our analysis since we would, ideally, have preferred to use utility-level sales data to capture the effect more precisely. It would be interesting to obtain more disaggregated sales data to have a more accurate picture of rebate programs even though, on average, we would expect the effect to be about the same. There have been relatively few papers that have an *ex-post* analysis of specific DSM programs. Our aim was to take one particular aspect of DSM and analyse its cost-effectiveness. The study of other DSM components should be the agenda for future research. There are many supporters and a few opponents of DSM and it is important to resolve the argument about the benefits of DSM.

In my second essay I analyse the presence of spillovers in pollution by looking at emissions and changes in emissions; that polluting facilities around other neighbouring facilities tend to have a similar environmental performance. I use information about location of each facility and exploit the variation in the emission levels and emission changes in a large sample of manufacturing facilities in Canada by using a simple and parsimonious spatial autoregressive (SAR) model and an extension of the SAR model that uses two spatial weight matrices instead of the traditional single spatial weight matrix. The "distance" between facilities is measured by the geographical distance as well as the closeness of a facility's SIC code with that of its neighbours. Spatial dependencies may be the result of both these factors and the extension of the SAR model takes into account both these channels simultaneously. I find that, compared to OLS results, spatial dependencies exist and are significant as indicated by the statistical significance of the spatial autoregressive parameters. My results also indicate that the effect of the industry SIC distance is substantially stronger than that of geographical distance.

There is much scope for further research in analysing environmental performance by using spatial econometrics. I have used the simple SAR(1) model and its modification to study spillovers. Its highly parsimonious and fully parameterized nature is an advantage but also an Achilles heel. The limitations of the SAR model, as discussed by Pinkse and Slade (2010), include the fact that the relationship may be non-linear, the error term and independent variables may be dependent and that the entire spatial dependence structure can be represented by the the spatial lag parameter ρ. Using different specifications would also serve as a test of robustness for the SAR model. There is also a case of combining the geographic distances with industry measures of distance, like the SIC codes, to compute a more sophisticated weight matrix that captures more aspects of "distance" than just the physical distance. In this essay I have considered two separate weight matrices to indicate the two separate channels through which spatial dependency may arise. The availability of panel data, as is the case with most toxics release inventories, is also suited for using spatial panel methods for further analysis. The disadvantage of using panel data is the change that might occur over a period of time in terms of new substances added or old substances removed from the list of reporting criteria as well as new facilities being asked to report. However, spatial panel econometrics is an area of active research and using these new methods would provide more robust and innovative ways of looking at spatial dependencies in emissions or other variables of interest.

In the third essay I use firm-level characteristics to predict the lobbying and abatement decision of firms in a model with two non-cooperating firms. There are three sources of firm heterogeneity, viz. the marginal cost of production, the emission intensity and the marginal cost factor of abatement. The decision to lobby or abate or do both depends on the cost-effectiveness of lobbying against that of abating. I find that a firm will abate and not lobby if its effective marginal abatement cost, which depends on output, is lower than a threshold value. An interesting outcome is that, under my assumption of perfect and complete information, the model predicts that in most cases the firm with the lower effective marginal abatement cost will not lobby but will free-ride on the lobbying effort of the other firm.

A variation of the current model would be to introduce an emission cap on the total pollution emitted rather than a standard on the emission intensity. Apart from abatement activities all other sources of firm heterogeneity are observable so it would be very interesting to apply the model for testing the predictions. However, as noted by Antweiler (2003), it is very plausible that there exists a high degree of negative correlation between abatement cost factor and the emission intensity if pollution abatement is dependent on plant vintage. While there may be other issues in the transition from theory to the empirical implementation, the model in this essay is an attractive starting point in analysing the abatement and lobbying decisions of different kinds of firms. There are some other avenues as well that I would like to explore in the future. There is the issue of side payments that firms may make to one another as “bribes” to reduce their pollution if a total emissions cap is in place. This could happen if the marginal cost of the dirty firm is sufficiently high so that it finds it more profitable to encourage the other firm to lower its emissions.

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Appendix A

Appendix to Chapter 1

A.1 Clothes Washers

Clothes washers have been in the Energy Star program since 1997. There were no US manufacturers whose washing machines satisfied the Energy Star standard when the program was proposed in 1994 by the US Department of Energy (DOE). This announcement caused a sharp division within the industry because the majority of the qualified products, being horizontal-axis (h-axis) washers[40], were being produced by European manufacturers. The first Energy Star qualified model produced by one of the large US manufacturers was the Neptune model from Maytag. It was released in the market in June 1997 and was, not surprisingly, an h-axis washer. However, its price was nearly double that of a standard v-axis model. Prior to the introduction of the Neptune market penetration for Energy Star qualified washers was less than one percent. Other US manufacturers jumped on the bandwagon and more Energy Star qualified washers were introduced and led to utility and regional efficiency groups offering rebates and incentive promotions on these energy-efficient washers. The Energy Star Clothes Washers program has led to a significant increase in innovation and technological advancement in the clothes washers industry.

Even within energy-efficient washers there is considerable variation in energy and water consumption. The energy efficiency is indicated by the Modified Efficiency Factor (MEF) that replaced the older Energy Factor (EF) rating in 2004. The MEF takes into account the projected dryer usage

[40]Horizontal-axis design is the industry term for front-loading washing machines while vertical-axis (v-axis) design refers to top-loading machines. There are, however, some h-axis machines that are top-loading. The most well-known models are produced by Staber Industries. New v-axis designs that use sprayers to wet the clothes from above can also achieve substantial energy and water savings compared to conventional v-axis washers, but they may not clean clothes as effectively, according to Consumer Reports.

based on the remaining moisture content as well as the machine energy and water heating energy of the washer.[41] A washer that spins clothes drier will get a higher MEF rating than one that leaves more moisture in the washed clothes. A higher MEF therefore signifies a more energy efficient washer. There have been recommendations from utility and regional efficiency units to include the amount of water used to calculate the ENERGY STAR efficiency because some ENERGY STAR qualified washers use as much water as non-ENERGY STAR qualified ones. Water Factor (WF) measures the ratio of the quantity of water used in one cycle to the capacity of the washer. So, for example, if a clothes washer uses 40 gallons of water per cycle and has a tub volume of 4.0 cubic feet then the Water Factor for that particular machine would be 10.0. A washer that has a lower WF is more efficient than one having a higher WF. Adding a maximum WF requirement would ensure that ENERGY STAR models save both water and energy. This prompted the DOE to add a WF requirement to the existing ENERGY STAR standard for washers January 1, 2007 onwards. The current ENERGY STAR standard, therefore, consists of both a minimum energy-efficiency standard as well as a maximum water-efficiency standard of 1.72 MEF and 8.0 respectively. To be qualified as ENERGY STAR a clothes washer must have an MEF of 1.72 or above as well as a WF of 8.0 or below. The evolution of the minimum Energy Star and Federal standards is shown in Table A.1.

The table shows that there has been a gradual improvement in the energy-efficiency of clothes washers. The average EF in 2001 was 1.55 while the most energy-efficient washers had a range from 2.5 to 3.5 EF. The evolution of standards for ENERGY STAR qualified washers can be seen in Table A.2. The average MEF for ENERGY STAR qualified washers was 1.65 when the new MEF standard of 1.26 was introduced in the beginning of 2001. It increased to 1.70 in 2003 and further to 1.74 in 2004 before dropping very slightly to 1.73 in mid-2004 due to the introduction of new models at the minimum ENERGY STAR MEF level. But the average ENERGY STAR washer showed

[41] As per the ENERGY STAR website Frequently Asked Question on "What are Modified Energy Factor and Water Factor on the ENERGY STAR qualified clothes washers list?", MEF is the quotient of the capacity of the clothes container, C, divided by the total clothes washer energy consumption per cycle, with such energy consumption expressed as the sum of the machine electrical energy consumption, M, the hot water energy consumption, E, and the energy required for removal of the remaining moisture in the wash load, D. The equation is

$$\mathrm{MEF} = \frac{\mathrm{C}}{\mathrm{M} + \mathrm{E} + \mathrm{D}}$$

Table A.1: EVOLUTION OF EF/MEF STANDARDS

Date	Minimum ENERGY STAR Standard	Minimum Federal Standard
1997	EF$\geq$2.5	EF$\geq$1.18
January 1, 2001	MEF$\geq$1.26	EF$\geq$1.18
January 1, 2004	MEF$\geq$1.42	MEF$\geq$1.04
January 1, 2007	MEF$\geq$1.72, WF $\leq$8.0	MEF$\geq$1.26
July 1, 2009	MEF$\geq$1.8, WF $\leq$7.5	MEF$\geq$1.26
January 1, 2011	MEF$\geq$2.0, WF $\leq$6.0	MEF$\geq$1.26, WF$\leq$9.5

Source: DOE

an improved efficiency in 2005 with the MEF increasing to 1.78.

Table A.2: AVERAGE MEF LEVELS OF CLOTHES WASHERS

Year	Average non-ENERGY STAR	Average ENERGY STAR
2001	1.11	1.64
2002	1.13	1.90
2003	1.14	1.93
2004	1.15	1.77
2005	1.13	1.81
2006	1.14	2.05

Source: DOE

A.2 Dishwashers

The ENERGY STAR standard for dishwashers has had a rather chequered history since the label for dishwashers was announced in October, 1996. Even though it was introduced more than a decade ago there have been very few modifications to the ENERGY STAR standard. This resulted in a market share of more than 90%, in 2006, for ENERGY STAR-labelled dishwashers in spite of the DOE's policy to have the label only for appliances that are in the top 25% for energy efficiency in the respective product category. It is for this reason that suggestions have been made to make ENERGY STAR label more coveted and the criteria to be changed more frequently to account for the improvements made in the energy efficiency of appliances.

There has been only one revision of the Energy Star standard since the first criteria level was announced in 1996. The efficiency of dishwashers is measured in terms of the Efficiency Factor (EF) and the minimum EF for a dishwasher to be considered Energy Star was 0.52. This EF was 13% above the Federal standard. The next revision of the Energy Star standard was made on January 1, 2001 when the minimum EF was raised to 0.58. At that time this was 26% above the Federal standard that, incidentally, has not changed since May 14, 1994. A long overdue revision of the Federal standard will take effect in 2010.

The infrequency with which the standards for dishwasher were changed is reflected in the way the average efficiency of dishwashers has changed for both Energy Star as well non-Energy Star models. Table A.3 shows the evolution of the average EF for both types of dishwashers. We can see that the average EF for non-qualified models has not changed much and neither has that for qualified models.

Table A.3: Average Modified Energy Factor Levels of Dishwashers

Year	Average non-Energy Star	Average Energy Star
2001	0.46	0.58
2002	0.46	0.58
2003	0.46	0.58
2004	0.49	0.64
2005	0.52	0.63
2006	0.48	0.63

Source: DOE

A.3 Refrigerators

The Energy Star label for refrigerators was, like that for dishwashers, also announced in October, 1996. For refrigerators the Energy Star standard is set at a certain percentage below the federal standard for maximum energy consumption in each product class. The National Appliance

Table A.4: Average Efficiency of Refrigerators (Percent Better Standard)

Year	Average non-Energy Star	Average Energy Star
2001	0%	10%
2002	1%	10%
2003	1%	11%
2004	2%	16%
2005	2%	16%
2006	3%	16%

Source: DOE

Energy Conservation Act (NAECA) of 1987 enabled the US DOE to set federal standards for the maximum energy consumption on household appliances. When the Energy Star label for refrigerators was introduced the standard for one to be considered Energy Star was if it consumed 20% less energy than the 1993 federal standard in the same product category. Subsequent revisions of the Energy Star specification led to the standard being set at 10% less energy consumption in 2001, 10% in 2003 and 15% less energy consumption in 2004. As can be seen from Table A.4 the average Energy Star refrigerator is quite close to the Energy Star standard while the average non-Energy Star refrigerator is also quite close to the minimum federal standard.

Table A.5: Average Energy Use of Dishwashers & Refrigerators (in kWh/year)

	Dishwashers		**Refrigerators**	
Year	non-Energy Star	Energy Star	non-Energy Star	Energy Star
2001	700	555	540	450
2002	700	555	558	502
2003	574	455	558	502
2004	439	336	520	442
2005	413	341	520	442
2006	448	341	525	457

Source: D&R International Ltd.

Table A.6: Random Effects Regression Models with Average Utility Rebates (2001 – 2006)

Variable	**RE1**	**RE2**	**RE3**	**RE4**
Intercept	-1.579^{a}	-3.392^{a}	-2.733^{a}	-.994^{a}
	(.045)	(.530)	(.336)	(.029)
CW*Rebate	.861^{a}	.580^{a}	.583^{a}	.265^{a}
	(.127)	(.105)	(.103)	(.068)
DW*Rebate	1.248^{a}	1.034^{a}	1.043^{a}	-.333^{a}
	(.218)	(.230)	(.230)	(.078)
RF*Rebate	.848^{a}	.508^{b}	.476^{a}	.053
	(.171)	(.210)	(.180)	(.079)
CW*Log Personal Income		.040	.041	
		(.040)	(.040)	
DW*Log Personal Income		.057^{c}	.058^{c}	
		(.031)	(.031)	
RF*Log Personal Income		.049^{c}	.053^{b}	
		(.027)	(.024)	
CW*Education		4.886^{a}	4.814^{a}	
		(.560)	(.565)	
DW*Education		1.106	1.043	
		(.736)	(.748)	
RF*Education		3.107^{a}	3.192^{a}	
		(.547)	(.520)	
CW*Log Electricity Price		.616^{a}	.606^{a}	
		(.158)	(.163)	
DW*Log Electricity Price		.562^{a}	.561^{a}	
		(.148)	(.154)	
RF*Log Electricity Price		.637^{a}	.514^{a}	
		(.101)	(.096)	
Appliance dummies	Yes	Yes		
Quarter*Appliance dummies			Yes	
Year-Quarter*Appliance dummies				Yes
Observations	3599	3599	3599	3599
Groups	50	50	50	50
R^2	.267	.34	.383	.888
χ^2-statistic	1375	2679	10946	8.8×10^5

Significance levels : ^{a}:1%, ^{b}:5%, ^{c}:10%, Standard errors clustered at the state level

Dependent variable is Log (Share of sales of Energy Star Appliances)

Utility rebate amounts re-scaled

Table A.7: Random Effects Regression Models with Average Weighted Utility Rebates (2001 – 2006)

Variable	**RE1**	**RE2**	**RE3**	**RE4**
Intercept	-1.493^{a}	-4.217^{a}	-3.305^{a}	$-.996^{a}$
	(.049)	(.591)	(.348)	(.027)
CW*Rebate	1.340^{a}	$.690^{a}$	$.676^{a}$	$.325^{b}$
	(.218)	(.148)	(.146)	(.127)
DW*Rebate	2.329^{a}	2.117^{a}	2.077^{a}	-.467
	(.643)	(.613)	(.591)	(.388)
RF*Rebate	1.408^{a}	$.774^{b}$	$.668^{c}$	.225
	(.478)	(.341)	(.343)	(.148)
CW*Log Personal Income		$.083^{c}$	$.085^{b}$	
		(.043)	(.042)	
DW*Log Personal Income		$.088^{a}$	$.090^{a}$	
		(.029)	(.029)	
RF*Log Personal Income		$.084^{a}$	$.086^{a}$	
		(.028)	(.025)	
CW*Education		6.068^{a}	6.003^{a}	
		(.615)	(.610)	
DW*Education		2.249^{a}	2.189^{a}	
		(.667)	(.669)	
RF*Education		3.831^{a}	3.873^{a}	
		(.552)	(.502)	
CW*Log Electricity Price		$.572^{a}$	$.555^{a}$	
		(.175)	(.179)	
DW*Log Electricity Price		$.512^{a}$	$.501^{a}$	
		(.135)	(.139)	
RF*Log Electricity Price		$.662^{a}$	$.540^{a}$	
		(.107)	(.099)	
Appliance dummies	Yes	Yes		
Quarter*Appliance dummies			Yes	
Year-Quarter*Appliance dummies				Yes
Observations	3599	3599	3599	3599
Groups	50	50	50	50
R^2	.240	.318	.361	.883
χ^2-statistic	1801	3668	15814	2.9×10^{5}

Significance levels : ^{a}:1%, ^{b}:5%, ^{c}:10%, Standard errors clustered at the state level

Dependent variable is Log (Share of sales of Energy Star Appliances)

Utility rebate amounts re-scaled

Table A.8: Peak Spot Prices for Major Pricing Points (in US$/MWh)

	On-Peak Spot Prices				Off-Peak Spot Prices			
	2003	2004	2005	2006	2003	2004	2005	2006
Northeast								
Mass Hub	59.05	61.47	89.87	70.33	41.80	42.94	61.79	47.45
NY Zone G	61.73	61.74	92.46	76.53	42.12	42.86	63.70	50.54
NY Zone J	77.82	76.63	110.03	86.47	48.70	48.28	72.61	55.05
NY Zone A	51.36	52.49	76.04	59.34	35.78	36.82	53.26	42.20
PJM West	48.49	51.10	76.64	62.92	24.14	30.15	40.72	36.36
Southeast								
VACAR	41.60	48.27	71.88	57.20	19.44	25.23	38.13	34.96
Southern	41.55	48.67	70.88	56.15	19.51	26.01	37.54	33.86
TVA	38.90	44.23	67.39	53.91	18.73	22.14	34.24	32.76
Florida	52.21	58.31	84.95	65.06	22.25	29.02	42.88	39.78
Entergy	41.47	45.76	69.95	56.65	18.39	23.04	38.02	34.06
Southeast								
Cinergy	37.57	43.31	63.76	52.39	15.91	19.88	29.12	29.93
ECAR North	38.41	45.58	67.13	55.94	16.54	21.00	30.84	29.30
MAIN North	43.14	47.94	64.70	58.67	16.47	20.28	28.78	25.73
NI Hub	37.11	42.03	61.76	53.15	15.44	17.57	28.71	28.35
MAIN South	38.43	42.85	63.38	51.73	16.06	18.41	28.70	25.54
MAPP North	45.18	47.06	65.06	58.67	17.22	19.12	28.57	25.73
MAPP South	43.29	45.90	65.48	55.56	16.93	19.00	28.01	32.61
South Central								
SPP North	41.66	45.19	67.44	56.23	18.48	20.55	34.82	33.91
ERCOT	46.49	47.32	70.95	58.74	30.51	31.45	47.95	39.09
Southwest								
Four Corners	48.55	50.51	69.39	58.79	32.28	35.45	46.74	36.45
Palo Verde	49.10	50.09	67.39	57.85	32.84	35.44	47.10	36.91
Mead	50.65	51.91	70.18	59.79	33.75	37.43	49.02	38.44
Northwest								
Mid- Columbia	40.73	44.54	62.95	49.52	34.04	39.27	50.21	37.23
COB	44.49	49.09	66.95	55.08	35.23	40.58	51.71	39.14
California								
NP 15	49.13	54.46	72.49	60.81	35.76	41.35	51.35	39.17
SP 15	51.25	55.20	73.03	61.77	35.15	39.26	51.22	40.07

Source: Federal Energy Regulatory Commission

Appendix B

Appendix to Chapter 2

B.1 Spatial Dependence Tests

Table B.1: LM Lag Statistic Tests for Spatial Dependence

	Levels		**Differences**	
Dependent Variable	**W1**	**W2**	**W1**	**W2**
CAC Emissions	14.722	292.118	0.060	10.434
	(0.000)	(0.000)	(0.807)	(0.001)
Health-indexed Air Emissions	0.204	57.82	0.234	0.267
	(0.652)	(0.000)	(0.628)	(0.605)
Health-indexed Total Emissions	3.135	230.255	1.329	47.533
	(0.077)	(0.000)	(0.249)	(0.000)

p-Values are in parentheses. Critical χ^2 values for the LM lag statistic tests are 2.71, 3.84 and 6.63 for significance levels 10%, 5% and 1% respectively. W1 and W2 are spatial weight matrices with $w_{ij} = (\text{geographical distance}_{ij})^{-1}$ and $w_{ij} = e^{-1*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

B.2 Spatial Regression Results

Table B.2: Spatial Regression Models for CAC Emissions

Variable	**Levels** W1 (1)	**Levels** W2 (2)	**Differences**† W1 (3)	**Differences**† W2 (4)
Intercept	12.123^a	-0.282	0.099	0.101
	(1.817)	(1.362)	(0.066)	(0.066)
Fraction of CEPA-regulated output	-1.276^a	-1.639^a	-2.107^a	-2.108^a
	(0.158)	(0.153)	(0.112)	(0.112)
Log of Employees	0.99^a	0.889^a	0.520^a	0.524^a
	(0.042)	(0.04)	(0.073)	(0.073)
Log of Population (1990)	-0.161^a	-0.177^a	0.206	0.215
	(0.028)	(0.024)	(0.162)	(0.162)
ρ	0.187^c	0.966^a	-0.021	0.480^a
	(0.081)	(0.071)	(0.094)	(0.028)
Province dummies	Yes	Yes	Yes	Yes
SIC dummies	Yes	No		
Adjusted R^2	0.4343	0.3658	0.1679	0.1675
Observations	2150	2150	2003	2003
Log-Likelihood	-3798	-3914	-408	-407
Spatial Multiplier, $1/(1-\rho)$	1.230	29.412	0.979	1.923

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (CAC Air Emissions). Standard errors are in parentheses. Specifications W1 and W2 are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-1}$ and $w_{ij} = e^{-1*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (3) and (4) should be interpreted as being differences.

Table B.3: Spatial Regression Models for Health-Indexed Air Emissions

Variable	**Levels**		**Differences**†	
	W1	**W2**	**W1**	**W2**
	(1)	(2)	(3)	(4)
Intercept	15.131[a]	1.390	0.044	-0.011
	(1.727)	(3.154)	(0.183)	(0.183)
Fraction of CEPA-regulated output	-2.238[a]	-2.617[a]	-3.944[a]	-3.947[a]
	(0.221)	(0.207)	(0.194)	(0.194)
Fraction of PSL-regulated output	-4.917[a]	-5.436[a]	-5.463[a]	-5.464[a]
	(1.06)	(1.078)	(0.527)	(0.526)
Log of Employees	1.071[a]	1.041[a]	0.376[c]	0.378[c]
	(0.084)	(0.077)	(0.192)	(0.191)
Log of Population (1990)	-0.229[a]	-0.256[a]	-0.726	-0.710
	(0.054)	(0.049)	(0.458)	(0.457)
ρ	0.080	0.867[a]	-0.001	-0.763[a]
	(0.065)	(0.16)	(0.088)	(0.057)
Province dummies	Yes	Yes	Yes	Yes
SIC dummies	Yes	No		
Adjusted R^2	0.3014	0.2649	0.2571	0.2569
Observations	1426	1426	1305	1305
Log-Likelihood	-3218	-3258	-1285	-1285
Spatial Multiplier, $1/(1-\rho)$	1.087	7.519	0.999	0.567

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (Health-Indexed Air Emissions). Standard errors are in parentheses. Specifications W1 and W2 are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-1}$ and $w_{ij} = e^{-1*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (3) and (4) should be interpreted as being differences.

Table B.4: Spatial Regression Models for Health-Indexed Total Emissions

	Levels		**Differences**†	
Variable	**W1**	**W2**	**W1**	**W2**
	(1)	(2)	(3)	(4)
Intercept	14.341^a	-0.154	-0.110	-0.059
	(1.641)	(1.202)	(0.213)	(0.213)
Fraction of CEPA-regulated output	-2.601^a	-2.992^a	-4.495^a	-4.495^a
	(0.199)	(0.183)	(0.228)	(0.227)
Fraction of PSL-regulated output	-7.501^a	-8.012^a	-6.376^a	-6.366^a
	(0.927)	(0.949)	(0.597)	(0.596)
Log of Employees	0.967^a	1.003^a	0.284	0.289
	(0.075)	(0.068)	(0.223)	(0.222)
Log of Population (1990)	-0.184^a	-0.255^a	-0.439	-0.402
	(0.049)	(0.045)	(0.514)	(0.513)
ρ	0.162^c	0.966^a	0.052^a	0.801^a
	(0.061)	(0.045)	(0.002)	(0.196)
Province dummies	Yes	Yes	Yes	Yes
SIC dummies	Yes	No		
Adjusted R^2	0.3710	0.3158	0.2367	0.2377
Observations	1641	1641	1516	1516
Log-Likelihood	-3663	-3723	-1776	-1774
Spatial Multiplier, $1/(1-\rho)$	1.193	29.412	1.055	5.025

Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b} and ^{c} respectively.
The dependent variable is Log (Health-Indexed Total Emissions). Standard errors are in parentheses. Specifications W1 and W2 are spatial regressions with $w_{ij} = (\text{geographical distance}_{ij})^{-1}$ and $w_{ij} = e^{-1*(\text{SIC distance})_{ij}}$ as elements in the weight matrices respectively.

†: For conserving space I have used the same variable names to report results from the difference specification. All regressors in columns (3) and (4) should be interpreted as being differences.