Empirical Essays in Water and Electricity Use

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

This thesis consists of three self-contained essays evaluating the impacts of educational attainment and average income at the community level on water consumption, the effects of different sources of energy on wholesale electricity rates and the effects of eliminating coal-fired electricity generation on air quality.

The first chapter looks at the impacts of educational attainment and average income at the community level on water consumption. The focus of this paper is on the three cities of Cambridge, Kitchener and Waterloo. In this chapter, we construct a unique household-level panel dataset that has monthly water consumption data of 22,000 households from 2012-2014. Our study shows that water consumption decreases as income at the Dissemination Area (DA) level increases. Our findings also show that educational attainment affects water use in a different way at different education levels in the following sense: increasing educational attainment at lower levels of education (from no certificate to high school certificate) increases water consumption, but the effect reverses when people receive post-secondary education. In addition, our study suggests that although education at different geographical levels affects household water consumption in different ways, there is a turning point where the explained relationship changes direction.

By creating and utilizing a unique panel data from the Independent Electricity System Operator (IESO) and Statistics Canada, over 2009 to 2014, the second chapter intends to analyze the effects of different sources of energy on wholesale electricity rates to see how the considerable shifts in electricity fuel mix since 2009 have impacted the Hourly Ontario Energy Price (HOEP) and Global Adjustment (GA). The study demonstrates that while less reliance on coal has resulted in an upward pressure on the HOEP, the increase in other sources of energy such as nuclear, hydro and wind power generations outweighed the effects of eliminating coal, which explains why the average HOEP fell from 26.4 $\$/MWh$ in 2012 to 23 $\$/MWh$ in 2014. On the other hand, the GA in terms of $\$/MWh$, rose by almost 50%. Although less coal is significantly associated with higher GA payments, we do not find that more wind and nuclear power generation have resulted in higher GA payments. In addition, our results show that more gas power is correlated with a reduction in GA.

Lastly, the third chapter uses the hourly air pollutant data associated with four cities of Toronto, Hamilton, Ottawa and Sarnia in addition to the data on hourly electricity generation from coal, gas, hydro, nuclear, wind and other (solar and biofuel) type of power plants for the period of 2009 to 2016. The pollution data are obtained from the Ontario Ministry of the Environment and Climate Change and the data on fuel mix are obtained from the Independent Electricity System Operator (IESO). We estimate the effects of hourly changes in fuel mix on Ozone (O_3), Nitrogen Oxide (NO_x), and Particulate Matter ($PM_{2.5}$) over a period in which coal-fired electricity generation was gradually eliminated from the electricity market. The paper also estimates the impacts of fuel mix on the probability of smog days. The results suggest that relative to coal, more nuclear and wind energy is correlated with decreased levels of NO_x and $PM_{2.5}$. In addition, an increase in nuclear powered generation is associated with reduced O_3 levels. On the other hand, the results suggest that in general, the correlation between different types of fuel mix and the elimination of smog days are not statistically significant.

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Dedication

I dedicate this thesis to my parents.

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Chapter 1

The Effect of Education and Income on Household Water Consumption: Evidence from the Tri-Cities of Cambridge, Kitchener and Waterloo

1.1 Introduction

Despite the importance of household water consumption behaviour, there remains a paucity of evidence on investigating the issue in different parts of Canada. Most studies have tended to focus on water conservation behaviour as a response to some technical changes driven by certain policy interventions rather than on water consumption behaviour that may vary depending on the underlying characteristics of a population. Only a handful of studies, such as Jorgensen et al. [2009] (in Australia) and Fullerton Jr et al. [2013] (in Canada), have studied the water consumption behaviour of households. In addition, while many studies have investigated the effects of household characteristics such as education and income on water consumption at the household level, there are fewer papers [1] on the effects of such attributes at the community level[2]. Although local government cannot directly impact a household's choice, it can use instruments such as community education to drive aggregated community-level choices in the planned direction. For example, in May 2014, the region of Waterloo prepared the "Water Efficiency Master plan (2015-2025)," with a goal "to engage municipalities, residents, businesses, and institutions in actions and behaviours that promote water efficiency and conservation." In this plan, general education and awareness was mentioned as one of the continuing activities at the residential sector that can implement these goals. In this regard, there is a need to understand the effects of various socioeconomic characteristics at the community level that interact with household water usage.

The focus of this study is on the impacts of educational attainment and average income at the community level on water consumption. This paper considers the Regional Municipality of Waterloo, which consists of the three cities of Cambridge, Kitchener and Waterloo, and the townships of Wellesley, Woolwich, Wilmot, and North Dumfries. However, because of data availability, the focus of this paper is on the three cities of Cambridge, Kitchener and Waterloo. While higher education results in significant private returns in form of increased income and better jobs, there is evidence that it is also correlated with more civic-minded choices (Milligan et al. [2004]). In other words, more educated people are careful about water consumption because of environmental concerns regarding the waste of natural resources. On the other hand, conservative or wasteful consumption practices by neighbours can impact the consumption patterns of adjacent neighbours. Therefore, looking at community-level educational attainment and income level is relevant to the extent that they represent not only individual but peer effects as well. While there exists a broad literature on household characteristics that affect water consumption, less work has been done on local characteristics that affect household water consumption. One reason is the difficulty of obtaining sufficiently detailed data that matches household water consumption with the corresponding neighborhood characteristics. We address these issues

[1]Readers can refer to research that are done by Fullerton Jr et al. [2013], Hurd [2006] and Domene and Saurí [2006], all of which are discussed in the literature review section of this paper.

[2]We will adopt a specific definition of a community and our results pertain to that scale only.

by constructing a unique dataset that relates available household water consumption to corresponding local educational level and income. In this paper, education at the Census Tract (CT) level[3] is expressed as the percentage of people in the area who have: no certificate/degree, high school degree, and post-secondary education. Average income is expressed at the Dissemination Area (DA) level[4].

The value added of this research stems from the availability of household-specific water consumption data from the three cities. As a result, we are able to construct a unique household-level panel dataset over time and thus control for the effects of unobserved and time-invariant household-specific attributes. The research data for this study is drawn from two primary sources: Statistics Canada Census data for 2011, and billing data for 2006-2014 from the three municipalities of Waterloo, Kitchener and Cambridge. The billing data, which is provided by the Water Services Division of the Region of Waterloo, consists of information for almost 100,000 households from 2006 to 2014. However, our final merged sample has monthly water consumption data of 22,000 households from 2012-2014. We are unaware of any other Canadian study that used data on a comparable number of households over time. In addition, most papers are unable to use detailed monthly panel data. Building knowledge on household water consumption behaviour in each neighbourhood can effectively lead policy makers to extend the culture of awareness for water conservation and consumption among the communities.

We acknowledge certain limitations to our data. We do not have educational attainment and income data at the individual level. It would be interesting to assess the effects of income and educational attainment on water consumption at the neighbourhood level when the data was aggregated from the household-level dataset. However, we have specific census-level data. In addition, while we have detailed information on water consumption dataset for the period of 2012-2014, the explanatory variables such as education and income (at CT and DA levels) are static and we are unaware of any changes to them that may have occurred during 2012-2014. The analyses are based on the most recent available dataset, and since there is aggregated data at CT and DA level, we believe that any changes would

[3]CT is a geographical unit with a population between $2,500$ and $8,000$ individuals.
[4]DA is a geographical unit with a population between 400 and 700 individuals.

be negligible and could not drastically change our results.

This study provides new insights into the effects of overall educational attainment and average income in each neighborhood on household water consumption. Much of the available literature on water consumption deals with the question of how higher- or lower-educated people make different choices regarding water consumption, and how income affects water consumption at the household level. In this study, we answer these questions at local levels. While other studies show a positive relationship between household income and water consumption, our study shows that water consumption decreases as income at the DA level increases. Our findings also show that educational attainment affects water use in a different way at different education levels in the following sense: increasing educational attainment at lower levels of education (from no certificate to high school certificate) increases water consumption, but the effect reverses when people receive post-secondary education. In addition, our study suggests that although education at different geographical levels affects household water consumption in different ways, there is a turning point where the explained relationship changes direction. A strong correlation between consumption patterns and neighborhood characteristics provides a credible justification for local government investment to design different policies that are tailored for different neighbourhoods.

This paper begins with a brief overview of the literature on household water demand and conservation behaviour in the second section. It will then go on to the data description in the third section. The fourth section details the empirical model used for this study, and the fifth section discusses the findings of this research. The sixth section concludes the paper with a summary of key points.

1.2 Literature

1.2.1 Socio-demographic variables that affect water consumption

Over the past few decades, researchers have investigated the effects of different socioeconomic variables to explain household water usage behaviour. Several studies have looked at the impacts of relevant socio-demographic variables including education and income, the number of residents in each household, stage of life (being retired or having teenage children), block-size and swimming pool ownership. In general, the literature shows that some of these variables are statistically more significant than others. In addition, these studies are carried out using individual or household level datasets.

Household income has been considered an important determinant of water consumption and conservation behaviour by many authors. Examples include De Oliver [1999][5], Syme et al. [2004][6], Cole [2004][7], Corbella and Pujol [2009], Grafton et al. [2011][8] and Fielding et al. [2012][9]. They all find a strong relationship between income and water consumption. Some of these studies, such as Syme et al. [2004], Cole [2004] and Fielding et al. [2012], find that households with higher income use more water. As noted by Cole [2004], this is primarily because higher-income families enjoy more water-consuming appliances. Similarly, the prevalence of water-intensive outdoor applications such as lawn gardens and swimming pools are evident among high-income families, which in turn increases their water consumption . However, not all studies find a significant relationship between income and consumption/conservation. For example, when considering household water conserva-

[5]The study is based on 203 census tracts for 22 consecutive months (July 1995 - March 1997) in San Antonio, Texas.

[6]The study is based on survey data from 397 households in Perth, Western Australia. The data is for 16 months (Summer 1998 - end of Summer 2000).

[7]The data for this study was provided by the World Bank, and it is based on the regional forecast of per capita consumption for the period of 2000 - 2020 on different world regions.

[8]They used "2008 OECD Household Survey on Environmental Attitudes and Behaviour" in this study which contains data for almost 10,000 households in ten OECD countries.

[9]The study was conducted based on survey data collected in south-east Queensland, Australia. It contains water consumption information for 1008 households from October 2009 to March 2010.

tion behaviour based on 431 households in Concord, New Hampshire, Hamilton [1983][10] finds that the direct and indirect effects of income cancel each other out; as a result, he concludes that income cannot be considered a good predictor of water conservation .

Other researchers have considered different variables as proxies for income. For example, in their study of household water consumption in Halifax, Fullerton Jr et al. [2013][11] use labour market variables, such as employment per capita, as the proxy for personal income. They observed how high levels of employment could give rise to water consumption in this region ; however, they used 52 observations to draw that conclusion. Some other researchers have considered an index of wealth that can be adopted as a proxy for income. Specifically, property value ("fiscal value of the dwelling as recorded in the urban property register" (Arbués et al. [2010])) has been considered in the literature as proxy for income. Some examples are Dandy et al. [1997][12], Aitken et al. [1994][13], Arbués et al. [2004] and Arbués et al. [2010][14]. All of these studies found a positive relationship between water consumption and property value . However, property value might be affected by variables that income would not be affected by; for example, the construction of a public transit line in a neighbourhood could increase property value but not household income. Therefore, property value as a proxy for income should be used cautiously.

On the other hand, studies that focus mostly on defining residential water demand typically consider some sort of water price to be the primary variable that can determine household water consumption behaviour. Such research not only examines the direct effect of price itself, but also considers the impact of price in response to changes in other variables, such as household size and income. For example, Arbués et al. [2010] study household sensitivity to price changes at different levels of household sizes, while Ren-

[10] The study applies the water use in five successive summers from 1978-1981

[11] The dependent variable in this study is the total municipal water used for the second quarter of 1996 to the first quarter of 2009. So, the dataset contains 52 observations in total.

[12] Data on yearly water consumption for 320 households in Adelaide, South Australia was gathered from the billing records of 8 years (1985-1992). Income information, however, is based on the survey data.

[13] Survey data is collected from almost 260 households in Melbourne, Australia during June, July and August (winter months) of 1991.

[14] For both studies, the dataset contains information on almost 1500 households during 1996 to 1998 (10-time observation for each household). The data for both studies are obtained from the Zaragoza City Council in Spain.

wick and Archibald [1998][15] and Renwick and Green [2000][16] examine different income class household responsiveness to price changes. Arbués et al. [2010] show that although households are sensitive to price changes regardless of sizes, smaller households are more sensitive. Renwick and Archibald [1998] and Renwick and Green [2000] demonstrate how lower income households are more sensitive to price changes. The key finding of the literature is that although income has a significant effect on household water consumption, consideration of price as an explanatory variable depends on the evaluated sample.

There are also studies that look at the impact of dwelling type (detached or attached) and residence size in determining household water consumption. Studies conducted by Aydinalp et al. [2004], Olmstead [2009] and Grafton et al. [2011] are some prominent examples. Aydinalp et al. [2004][17] and Grafton et al. [2011] control for type of residence when studying household water consumption, and Olmstead [2009] focuses mostly on residence size. It is a common hypothesis that households with larger houses are expected to have higher water consumption. An example of this is Grafton et al. [2011], who use housing survey data for ten countries. Their results confirm the positive sign of residence size on household water consumption Grafton et al. [2011]. In addition, earlier, Olmstead [2009][18] studied both house square footage and lot square footage. She finds that house square footage has a positive and significant effect on household water demand.

Moreover, Fielding et al. [2012] examines the effect of socio-demographic variables such as household size, income, education, age and gender on water consumption. Among these variables, household size "emerged as the strongest predictor of household water use"

[15] The dataset for this study has been gathered from the monthly bill of 119 households for six years (1985 to 1990) in Goleta and Santa Barbara, California. Each household then took part in telephone survey regarding their income, number of people per household and so forth.

[16] Monthly agency-level data from 1989 to 1996 for eight urban water agencies in California is used in this study (Number of observation: 776).

[17] This study is based on the 1993 survey of household energy use (SHEU) database. The dataset contains information on house characteristics for 8767 households from all provinces of Canada; however, the authors use 2749 households for which the energy billing data exist.

[18] This study uses the survey data on 671 households in 1998 in seven areas of the United States and Canada. In addition, household consumption is observed for four weeks (two weeks of dry and 2 weeks of wet seasons) and the daily average for every two weeks represents the total consumption for that billing period.

(Fielding et al. [2012]). Aitken et al. [1994] considered variables including property value, clothes washing machine loads, dish washing machine loads, the number of toilets, the number of showers per week and number of people per household. After running stepwise regressions, they found that the most suitable model was the one that considered three variables: property value, clothes washing machine loads, and number of residents per household. This model explains 60% of variation in data ($R^2 = 0.6$). Furthermore, they find that number of residents per household is the strongest predictor of water consumption in their model.

On the other hand, according to Jorgensen et al. [2013][19], a key shortcoming in most of this literature is a lack of data over time. Thus, -in their contribution- they focus on the dynamics of water consumption over time. Their findings support the hypothesis that household-level variables, as suggested by previous literature, are significant predictors of consumption. However, only household size is a consistent predictor of initial water consumption .

The effects of other social characteristics such as education and home ownership have also been researched. The importance of education has been widely examined in papers that are concerned with analysing water conservation behaviour. An example is a study by Geller et al. [1983][20], which develops an educational approach that examines the effect of installing water-conserving appliances on household consumption. The effectiveness of education is also exemplified in research by Hamilton [1983]. He argues that income and education, however pivotal, cannot show any significant effect on water conservation behaviour since their direct and indirect effects cancel each other out. Hamilton's findings are supported by De Oliver [1999], who focuses on census tract-level data from San Antonio, Texas. He shows that income and education are highly correlated in this district and both have negligible effects on conservation behaviour.

Although extensive research has been carried out on the effects of socio-demographic

[19]Dataset consists of descriptive information on 615 households in two Australian states for four quarters in 2009 and 2010.

[20]In Summer of 1982, 129 residents of Blacksburg, Virginia volunteered to participate in this study for 70 consecutive days.

variables on household water consumption, this research has been mostly restricted to data over a short period of time. In addition, the research to date has tended to focus on a small number of households. On the other hand, the impact of socio-demographic variables at the community level on household water consumption remains unclear. Most studies have only focused on survey data at the household level. Although understanding household behaviour helps to manage water conservation practice, policy makers need to know the household characteristics and the extent to which each characteristic affects water consumption in their service area in order to better plan water conservation programs.

1.2.2 Effects of peer behaviour on household water consumption

Research into water conservation psychology conducted by Corral-Verdugo et al. [2003][21] shows how environmental beliefs, such as utilitarian and ecological beliefs regarding water availability in nature, affect water conservation. In their study, the structure of environmental beliefs has been broadened to include beliefs about "1) the need for maintaining a "balance" with nature, 2) the need for imposing "limits" to human growth, and 3) a human exception paradigm (HEP)" (Corral-Verdugo et al. [2003]). Results from their survey of 510 individuals in northern Mexican cities suggest that whereas utilitarian water beliefs tend to be more concerned with HEP, ecological water beliefs are affected negatively by HEP and positively by limits. Furthermore, utilitarian water beliefs pursue more water consumption behaviours; by contrast, ecological water beliefs discourage such behaviour.

More recently, Jorgensen et al. [2009] trace the social and economic models that describe household water consumption. They argue that while concerned with different sets of variables, the literature lacks the consideration of trust in household water use. For Jorgensen et al. [2009], trust refers to both "interpersonal" and "institutional" trust. They highlight the fact that "trust in water authority and trust in others in community (including different water using sectors, such as farmers, residents and industry) to take steps to reduce their

[21] This study uses survey data on 510 individuals living in two Mexican cities. In addition to demographic information from the survey, water usage information is gathered from the water bill for each family. The authors then generate individual-level water usage data by dividing the total consumption by family size.

water consumption will increase the likelihood that people will also take steps to reduce their water use" (Jorgensen et al. [2009]). One of the examples of households' beliefs about water consumption can be seen in the study conducted by Troy et al. [2006][22] in Sydney, Australia. Their study suggests that only 7% of households guessed that their consumption was above an average Sydney household, and almost half of households thought they were below the average consumption level.

With regard to household consumption patterns, one of the sub-areas that attracts interest is external water use. Such studies have considered the effect of lawn and garden watering usage and swimming pool ownership on water conservation and consumption. As Dupont and Renzetti [2013][23] emphasise, lawn and garden watering can increase a household's total water consumption by 50%. Similarly, Domene et al. [2005][24] conclude that on average, gardens use 30% of the annual household water consumption, and this amount can increase to 50% in summertime in Barcelona. Further, Mini et al. [2014][25] study residential outdoor water uses in Los Angeles, California; they highlight that 54% of water use in the city has been allocated to landscape irrigations. The effect of home garden watering is exemplified in work undertaken by Syme et al. [2004]; Not surprisingly, they find that better gardens use more water .

Given household external water use (specifically watering gardens and lawns) and factors that affect household water use from the psychological point of view (such as "trust," as mentioned by Jorgensen et al. [2009]), a question arises. Is it possible that the choice of one neighbour regarding watering lawns and gardens affects the choice of others? In other words, does one neighbour's greener garden persuade other neighbours to have greener gardens?

[22]The data used in this study is from a large-scale telephone interview survey of 2179 people in Sydney, Australia from December 2004 to May 2005.

[23]The main data source of this study is the Statistics Canada's 2006 Households and the Environment Survey" and the final sample consists of 9479 households.

[24]The study is based on 120 interviews with homeowners in six municipalities of Barcelona, Spain during April to October 2001

[25]The dataset for this study consists of monthly water data for households residing in 855 census tracts in the city of Los Angeles for a ten-year period (2000-2010). The water billing and lot size data are collected from the Los Angeles Department of Water and Power.

Some researchers have touched on this issue, but none, to the best of our knowledge, have yet accomplished the study of such relationships. Hurd [2006][26] shows that the landscape of neighbours is one factor affecting landscape choice. Nevertheless, Hurd's primary focus is on other factors, such as water prices and level of public education. For example, his results indicate that choices about landscape type are sensitive to water prices. In the same vein, recently Bollinger et al. [2018] find that a 10% change in neighbour's landscape greenness results in a 1.4% change in the households landscape greenness. However, their research show that such peer behaviour are completely driven by economic incentives. Domene and Saurí [2006][27], by contrast, found a positive effect of household income rather than an adverse effect of water prices on outdoor water use in Barcelona. Peer effects are also considered in the research done by Bollinger and Gillingham [2012] on the adoption of solar panels. Bollinger and Gillingham [2012] find that the probability of installing a solar panel in a zip code increases by 0.78 percentage points with an extra installation in the zip code[28]. It is also worth noting the studies and datasets on water consumption and conservation behaviour that have been used so far in Canada. These studies are outlined in the following subsection.

1.2.3 Canadian Literature

In their empirical analysis of water consumption in Halifax, Fullerton Jr et al. [2013] use data from Halifax Regional Water Commission, Environment Canada and Statistics Canada. Specifically, they collected data for municipal water consumption in cubic meters from the Halifax Regional Water Commission, weather data documented by Environment Canada, and employment and price index data reported by Statistics Canada. The authors study the long-run and short-run dynamics of water consumption in Halifax. They investigated the effects of weather and price on municipal water consumption and find

[26] 423 single-family dwellings responded to the questionnaire that was mailed to them. The respondents were chosen randomly in three cities in Mexico during the summer of 2004.

[27] Dataset contains information on 532 households in 22 municipalities of Barcelona. Households responded to telephone questionnaires, and the interviews were conducted from January to March 2004.

[28] The dataset for this study consists of 85,046 households who requested solar panel installation from January 2001 to December 2011 in San Francisco, California.

that consumption is price inelastic. They calculated the municipal water consumption at a given time by dividing the total water consumed or sold by the number of municipal utility customers at that time. Therefore, they did not use the historical data for individual consumption. Besides, they only considered the metered water in their calculation and therefore the dependent variable (municipal consumption per customer) does not account for any sort of water leakage. Moreover, Fullerton Jr et al. [2013] did not consider any socio-demographic variables such as income and education that can differently affect the regions within the Halifax municipality.

Olmstead et al. [2003], in their study of water demand, analyzed the household data in eleven urban areas in the United States and Canada, including the Waterloo-Cambridge region. Data on socio-demographic variables such as gross annual household income, family size, home age and size were all collected through an anonymous one-time household survey. The dataset consists of information on 1082 households. As Olmstead et al. [2003] state, "households chosen for the study were randomly sampled from a subset of utilities' customer database: residential single-family households" (Olmstead et al. [2003]). They focused on different price structure and its impact on residential water demand. They found significant difference in water demands between households facing increasing block prices versus households facing uniform marginal prices. However, they are unsure if the difference is solely due to price structure or to the heterogeneity in utility service area.

Dupont and Renzetti [2013] use Statistics Canada's 2006 Households and the Environment Survey (HES) to assess the effects of various socio-demographic variables on decisions over conservation. HES contains information on household's income, the number of household members, the highest level of education of the respondent, the city or town in which the household is located, and other variables that describe indoor and outdoor water conservation choices . They combined HES with the Labor Force Survey (LFS) conducted in 2006 to identify the outdoor conservation choices that are made under price and non-price conservation policies. Specifically, they focus on the frequency of lawn and garden watering to investigate the conservation behaviour of households. They find that price affects household decisions regarding indoor water conservation more than outdoor water conservation. In addition, they show higher income and education have positive affect on water conservation. A main drawback of their study, however, is the small sample size. They combine different datasets, resulting in a sample of around 10,000 households all over Canada which is less than one percent of Canada's population in 2006. Tables 1.1 and 1.2 summarize some of the more recent studies on water consumption in and outside of Canada.

As was pointed out in the introduction to this paper, most studies on water consumption are limited to household surveys, and the units of analysis in these studies are individuals. Socio-demographic variables considered in these studies, such as education and income, are at either the individual or household level. However, the aim of this paper is to explore the relationship between household water consumption and local characteristics. This study intends to determine the extent to which local characteristics affect water consumption patterns of households that are living in the same neighbourhood. In particular, we test the hypothesis that local characteristics affect household-level behaviour and proxy peer behaviour.

1.3 Data Description

1.3.1 The Tri-Cities Socio-demographic Description

The Tri-Cities of Cambridge, Kitchener and Waterloo are located in Ontario, Canada. According to Statistics Canada, Waterloo is the smallest of these three cities. Some relevant characteristics of the Tri-Cities are summarized in Table 1.3. This table provides the breakdown of educational attainment and some of the economic features of these three cities. Based on the statistics provided in Table 1.3, Cambridge and Kitchener are very similar in terms of population education. In addition, the median income in Cambridge and Kitchener are very close. On the other hand, Waterloo has a higher-educated population and, unsurprisingly, higher median income[29].

[29] http://www12.statcan.gc.ca/nhs-enm/2011/as-sa/fogs-spg/Pages/FOG.cfm?GeoCode=3530010&lang=E&level=4

1.3.2 Data Collection

Based on the submission of our research proposal, we were able to obtain confidential water usage data for the three municipalities in the region of Waterloo. Subsequently, the data was released by the Water Service Division in the Region of Waterloo. The dataset for these regions includes annual water consumption of over 100,000 houses from 2006 to 2014. For some years and some municipalities, we have more detailed information, such as monthly consumption, average and peak consumption for the year. For the city of Waterloo, yearly total consumption for 2006 to 2014 and monthly consumption from 2007 to 2014 are reported in the dataset. The dataset for the city of Kitchener contains both monthly and yearly total water consumption from 2006 to 2014. However, for the city of Cambridge, monthly consumption is not reported for all years; the dataset for this city has total consumption for all years from 2006 to 2014 (except 2011) and monthly consumption from 2012 onward. We also gathered information on the characteristics of each house from the Residential Building Permits dataset for the Waterloo Region. This dataset contains house sizes and the value of each house when it was registered in the database. The data was provided by the City of Waterloo and is accessible at the Geospatial Centre in the University of Waterloo.

The next step was to merge the two datasets. The unique longitude and latitude coordinates of each house are available from all datasets. However, the point of origin for the first dataset (water consumption dataset) was different than the point of origin for the second dataset (Residential Building Permit dataset). The longitude and latitude coordinates in the first dataset were reported based on a local point of origin which was fixed by the Waterloo municipality; this was different from the standard point of origin on the map. Using the "Location Hub" software provided by the Geospatial Center in the University of Waterloo, we found the standard longitude and latitude for the data points of the first dataset. Next, we merged two datasets to construct a unique dataset of 21,756

http://www12.statcan.gc.ca/nhs-enm/2011/as-sa/fogs-spg/Pages/FOG.cfm?GeoCode=3530013&lang=E&level=4

http://www12.statcan.gc.ca/nhs-enm/2011/as-sa/fogs-spg/Pages/FOG.cfm?GeoCode=3530016&lang=E&level=4

houses in the Tri-Cities. Only some of the houses are included in both of the datasets; therefore, some of the observations were dropped in the merging process. Table 1.4 shows the distribution of houses in these three municipalities.

The next step involved matching houses with the local characteristics of neighbourhoods within the dataset. In particular, we were interested in education level and average household income[30] in different neighbourhoods. We used the Statistics Canada dataset on local characteristics. Based on the Statistics Canada 2011 Census data (the most recent census data), houses in the newly constructed dataset are located in 91 Census Tract (CT) areas and 401 Dissemination Areas (DA). A DA is a geographic unit with a population of 400 to 700 individuals, while CT is larger and has a population between 2,500 and 8,000 individuals. Figure A.1 in the appendix shows the map of the study area with the DA divisions.

Each CT has information on: 1) total population aged 15 years and older by highest certificate, diploma or degree; 2) number of people who have no certificate, diploma or degree; 3) number of people who have a high school diploma or equivalent; 4) number of people who have a post-secondary certificate, diploma or degree. In addition to education, we searched for the average income data at neighbourhood level. We found that the average income data is based on the DA decomposition. More specifically, the average income of population aged over 15 years and over in 2010 was reported at each DA. This data was also collected from Statistics Canada.

To merge the datasets for education, income and houses, we used tools within the "Arc GIS 10.3.1" software provided by Geospatial Centre in the University of Waterloo. We successfully pinned the education data on the City of Waterloo map first. Afterwards, using the same software, we pinned the houses on the same map by using longitudinal and latitudinal information for each house. Then, in the last stage, we extracted the information for each house from the constructed map. We repeated this three-stage procedure to gather the average income data at the DA level. The same process was followed to extract the education and income information for each city. Figure A.2 in the appendix shows

[30]We think that these levels are small enough so that we do not expect significant heterogeneity within a neighbourhood that might give rise to aggregation effects (in which we miss some variations in the dataset).

the geographical distribution of houses in the dataset across the Tri-Cities. More vivid maps are shown by Figures A.3 to A.5, with both different geographic divisions and house distributions for each city.

1.3.3 Data Summary

A detailed summary description of the dataset that was used for this study is reported in Table 1.5. In our dataset, household water consumption data is quite detailed. This dependent variable has yearly information from 2006 to 2014 (except for the city of Cambridge, which does not have the data for 2011). Specifically, the dataset for the city of Waterloo has bimonthly billing information for water consumption, whereas the cities of Cambridge and Kitchener have monthly water consumption reported. In order to have a balanced panel, we used only bimonthly consumption data for the cities of Cambridge and Kitchener as well. Thus, there are 6 consumption values collected for each house in each year. On the other hand, the main independent variables (educational attainment and average income) carry the information at the CT and DA level. These are gathered from the 2011 Census data. Therefore, we focused on the more recent period of 2012 to 2014 for which the water consumption data is available for all three cities.

As explained in the Data Collection subsection, the number of houses in the final merged dataset is around $21,000$, whereas we have water consumption data for $100,000$ houses. Therefore, we scrutinize both the first dataset (taken from the Water Service Division in the Region of Waterloo that contains around $100,000$ houses) and the final merged dataset. In the final dataset, the minimum and maximum of average water consumption are 1 m^3 and 742.3.759 m^3, respectively. In the first dataset, the minimum and maximum of average water consumption are 0.6666 m^3 and 62234.61 m^3, respectively. However, in the first dataset there are only two houses that have minimum average water consumption lower than 1 m^3 (final merged dataset minimum) and 204 houses that have maximum water consumption greater than 742.3.759 m^3 (final merged dataset maximum). This number of houses is negligible when compared to the total number of houses, and shows that the final dataset is reliable in the sense that it contains houses representing the average water amount patterns of most of the houses in the first dataset. Table 1.6 shows the summary statistics of first dataset in detail.

The data for the average income per year is divided by 1000, so it is reported in 1000 dollars per year. As seen in Table 1.5, average income varies from $17,025.00\$$ to $97,376.00\$$ per year. In this dataset, 139 houses are reported to have an average income lower than $10,000.00\$$. This accounts for only 0.63% (less than 1%) of houses that are considered in this study. To prevent these outliers from changing the results drastically, we dropped these houses. Since the number of dropped houses is less than 1%, the results are still robust.

The average income data is at the DA level. Therefore, we have 401 different average income values. In order to see the relationship between income and water consumption, we decided to plot the two columns of data against each other; however, before that, we aggregated the data at Census tract level. Therefore, there are 91 observations that are shown in Figure 1.1. To plot this graph, we preferred to have a low number of points so that they can be clearly seen. Most of the data points in this case are at the bottom left corner of Figure 1.1; this area of the figure is associated with low income and low consumption. However, it is important to note that the income variable is at the DA level through our entire empirical analysis.

The percentage of people who have no certificate, high school or post-secondary certificate in each CT are calculated by dividing those numbers by the total population in each CT. Figures 1.2 to 1.4 compare the breakdown for each level of education and their distribution in the Tri-Cities. From the first set of histogram distribution graphs in Figure 1.2, it is apparent that the percentage of Census Tract areas in which few people have any form of certification decreases when we move from Cambridge (at the top part of the figure) to Waterloo (at the bottom). This further confirms that the city of Waterloo has relatively few people with low levels of education.

Figure 1.3 shows the distribution of the percentage of people who have high school degrees in Census Tract areas of Cambridge, Kitchener and Waterloo. The same trend as in Figure 1.2 is seen in these sets of histograms. However, we cannot draw any conclusion solely by looking at these figures, as we do not know if the rest of population in each city is more or less educated. Figure 1.4 is quite revealing in several ways. Firstly, unlike the other two towns, in Waterloo, the percentage of Census Tract areas in which almost 68% of the population has post-secondary education is 58%. This reemphasizes the fact that most of the population in the city of Waterloo is educated. Secondly, the distribution of post-secondary education in Cambridge shows that the percentage of Census Tract areas in which 50 to 60% of people have post-secondary education is between 14% and 16%.

The observed statistics from these figures are all consistent with the educational attainment of the total population in Tri-Cities (refer to Table 1.3). Therefore, we can rely on inferences that are drawn from this sample, as it contains information about the characteristics of the Tri-Cities population.

1.4 Empirical Specification

The focus of this study is on the three cities of Cambridge, Kitchener and Waterloo. Based on Statistics Canada, each city is divided into small Census Tracts (CT) and smaller Dissemination Areas (DA). The division is based on the population in each region. This paper assesses the significance of individual level of education in each CT and income in each DA in determining water consumption patterns across the Tri-Cities[31]. In addition to educational attainment and income, other variables such as monthly precipitation and temperature[32] are also added to the model to capture any water consumption changes due to climate factors. What follows is an example to show why is it credible to work with the aggregated data.

In an extreme case, suppose that there are two houses studied in the geographical area. Every individual in both houses will consume water. Let's further suppose that there is an extreme level of disparity in education and in the number of people between the two houses. Assume that nine individuals are living in the first house and they all have less than high

[31] The multilevel analysis on page 21-23 considers the different aggregation levels that present in the dataset of this research.

[32] Available online at, http://climate.weather.gc.ca/

school education (no certificate), and there is one person living in the second house who has post-secondary education. In this case, the education level of the people in the first household strongly influences the average educational attainment in this area. Therefore, we can say that 90% of people in this area have less than high school education. Now, let's take the average of water consumption between these two households. If there exists a link between education and water consumption, then averaging the water consumption between the two households would still be affected by the education of people in the more populated house. As mentioned earlier, in this study, the considered explanatory variables for water consumption regressions are reported at the DA (in which 400 to 700 individuals live) and the CT (in which $2,500$ to $8,000$ individuals live) level. The dependent variable is at the household level. Since we are interested in dynamics of water consumption over time, we do not aggregate the water consumption at different geographic levels and consider the bimonthly water consumption of each household as a dependent variable. We propose and estimate the following function for family water consumption:

$$\mathrm{C}_{ijkl} = \beta_0 + \beta_1 AvgInc_{jkl} + \beta_2 PostSecondary_{kl} + \beta_3 NoCertificate_{kl} + \beta_4 AvgTemp_i + \beta_5 AvgPrecip_i + C + CT + Y + M + \varepsilon_{ijkl}$$
(1.1)

Where:

$i = 1, ..., 6$ Bimonthly.

$j = 1, .., 401$ Number of DAs.

$k = 1, ..., 91$ Number of CTs.

$l = 1, 2, 3$ Number of Cities.

C_{ijkl} = Bimonthly water consumption in $m^3/sqft$ (cubic meter per square footage) of household from 2012 to 2014 in the Dissemination Area (DA) j and the Census Tract area (CT) k and the City l.

$AvgInc_{jkl}$ = Average income of the households living in the DA j and Census Tract area (CT) k and City l.

$NoCertificate_{kl}$ = Percentage of population that has no certificate in the CT k and City l.

$PostSecondary_{kl}$ = Percentage of population that has a post-secondary degree in the CT

k City l.
$AvgTemp$ = Bimonthly average weather temperature based on degree Celsius $°C$.
$AvgPrecip$ = Bimonthly average precipitation based on millimetre (mm).
C = Set of dummy variables for the three municipalities of Cambridge, Kitchener and Waterloo.
CT = Set of dummy variables for Census Tracts areas (CT).
Y = Set of dummy variables for years.
M = Bimonthly set of dummy variables.
ε_{ijkl} =is an idiosyncratic error term.

The objective of this research is to determine whether education and income at the local level can affect household water consumption. In particular, we are interested in estimating β_1, β_2 and β_3, where the first β shows $m^3/sqft$ change in water consumption in response to 1000$ change of income in DAs, and the other two βs yield the $m^3/sqft$ change in the household water use in response to a one percentage point increase in the proportion of the population with post-secondary education and no certificate (relative to high school certificate) in the CT in which they live, respectively.

To run the regressions, we start from the basic model in which we do not control for any fixed-effects of municipalities, CTs, years or months. Then we proceed by using the fixed effect models in which we control for characteristics within each city or CT and further within each month and year. Moreover, we run the Ramsey Regression Equation Specification Error Test (RESET) to determine if the non-linear combination of independent variables can better explain the variation in the dependent variable. If we cannot reject the null hypothesis that the model has no omitted variables, then we can estimate the following model:

$$\mathrm{C}_{ijkl} = \beta_0 + \beta_1 AvgInc_{jkl} + \beta_2 AvgInc^2_{jkl} + \beta_3 PostSecondary_{kl} + \beta_4 PostSecondary^2_{kl} + \beta_5 NoCertificate_{kl} + \beta_6 NoCertificate^2_{kl} + \beta_7 AvgTemp_i + \beta_8 AvgPrecip_i + C + CT + Y + M + \varepsilon_{jkl}$$
(1.2)

The purpose of adding the squared values of the independent variables to the estimation is to consider the possibility that the relationship between dependent and independent variables wears off at a certain point. In this case, for example when interpreting the ceteris paribus effect of a change in post-secondary education on water consumption, we must look at the equation:

$$\frac{\delta C_{ijkl}}{\delta PostSecond_{jkl}} = \beta_3 + 2\beta_4 PostSecond_{jkl} \tag{1.3}$$

That is, we cannot interpret the β_3 in isolation. Solving equation 1.3 gives us the turning point of the relationship. If β_4 is negative, the relationship reflects an inverse U-Shape, and vice versa.

The above-mentioned linear models assume that the same intercept and slope characterize all three cities and all 91 Census Tracts; however, we want to make room for the tendency toward different consumption patterns across Cities and CTs. Therefore, we allow each City and each CT to have its intercept. We employ a Multilevel mixed-effects model, which reflects the multilevel structure of the dataset and allows each of the three cities and 91 Census Tracts to have its random intercept. Different authors have used this model to measure the random effects at each level of the dataset (e.g. Moshiri and Simpson [2011]; Walter and Block [2016]). We estimate the following mixed model:

$$\mathrm{C}_{ijkl} = \beta_0 + \beta_1 AvgInc_{jkl} + \beta_2 PostSecond_{kl} + \beta_3 NoCertificate_{kl} + \beta_4 AvgTemp_i + \beta_5 AvgPrecip_i + u_l + \varepsilon_{ijkl}$$
(1.4)

Where:

u_l = random intercept for City l

In this model, u_l is the unobserved city-level effect which allows for the possibility that the mean of water consumption varies among the cities. This seems appropriate given the geographical pattern of the dataset. The result of the proposed one-level mixed effect regression is presented in the first column of Table 1.15 (Reg (1)).

Furthermore, since the water consumption can vary across the CTs, we can control for the census tract effects in our regression by assuming census-tract to be another level in the hierarchical structure of the data. Therefore, we allow for two-level hierarchical model estimation (City-level and Census Tract-level). We estimate the following model:

$$\mathrm{C}_{ijkl} = \beta_0+\beta_2 AvgInc_{jkl}+\beta_3 PostSecond_{kl}+\beta_4 NoCertificate_{kl}++\beta_4 AvgTemp_i+\beta_5 AvgPrecip_i+ u_l + u_{lk} + \varepsilon_{ijkl}$$
(1.5)

Where:

u_l = Random intercept for City l

u_{lk} = Random intercept for Census Tract k of City l

We first run the regression that is shown in equation 1.4 treating City as one level of the hierarchy. Then, we add Census Tract as the second level and estimate the proposed two-level mixed model. This way, we incorporate the hierarchical structure into our model. By running this regression, we estimate the variability accounted for each level of the hierarchy. More specifically, u_l and u_{lk} quantify the average deviation at each level of the hierarchy. The results of the proposed one-level (equation 1.4) and two-level mixed-effect model (equation 1.5) are presented in the first and second column of Table 1.15 (Reg (1) and Reg (2), Part A), and they are discussed in next section.

We further aggregate the data at the household level and calculate the average water consumption for each house from 2012 to 2014. Therefore, in this case the dependent variable is at the household level, while the right-hand-side variables remain unchanged for each house. This dataset enables us to run the multilevel mixed effect regression when decreasing the volatility of the dependent variable, and to check the magnitude and sign of the estimated coefficients of interest. We run the following regression in this case:

$$\mathrm{AC}_{jkl} = \beta_0 + \beta_1 AvgInc_{jkl} + \beta_2 PostSecond_{kl} + \beta_3 NoCertificate_{kl} + u_l + \varepsilon_{jkl}$$
(1.6)

Where:

AC_{jkl} = Average water consumption in $m^3/sqft$ (cubic meter per square footage) of household from 2012 to 2014 in the Dissemination Area (DA) j and the Census Tract area (CT) k and the City l.

u_l = random intercept for City l

As before, we run the multilevel regression estimation in which we allow for two levels of hierarchy: city and CT. We run the following regression:

$$\mathrm{AC}_{jkl} = \beta_0 + \beta_1 AvgInc_{jkl} + \beta_2 PostSecond_{kl} + \beta_3 NoCertificate_{kl} + u_l + u_{lk} + \varepsilon_{jkl} \quad (1.7)$$

Where:

u_l = Random intercept for City l

u_{lk} = Random intercept for Census Tract k of City l

Since the data are averaged at the household level, we exclude the monthly climate variables from the regressions. Results of equation 1.6 and 1.7 are presented in Table 1.16 Part A.

In all cases, we also limit the analysis to the summer months. This enables us to see how the independent variables would explain changes in the dependent variable in the summer, when water consumption is usually higher. Unless otherwise stated, standard errors of all OLS estimates are robust. In this case, standard errors are calculated when we do not impose any assumptions on the structure of heteroskedasticity. As mentioned in the tables, in some cases, standard errors of OLS estimates are clustered at CT or DA level to account for within-cluster correlation or heteroskedasticity. In these cases, regression model errors are considered independent across clusters but correlated within clusters.

A limitation of our analysis is that although there is no direct reverse causality between the dependent (water consumption) and independent variables (educational attainment and income), it is possible that observed water consumption pattern might affect where people decide to live. This is because we are identifying the effect of education by location on water consumption. For example, a highly-educated person might decide to reside in an area where people do not waste water. In this case, the estimated coefficients of education variables would be biased, because they are also capturing mobility pattern among people. However, we think that these effects are negligible; when deciding where to live, people typically consider other criteria, such as safety or distance to workplace.

1.5 Empirical Results

This section presents the findings of the research. While other research relies primarily on self-reported household level data, our panel data allows us to identify the effects of household characteristics at different census levels on water consumption taken from billing data. Most of the literature suggests that there exists a positive relationship between income and water consumption at household level. In addition, we expect to see a negative relationship between educational attainment and water consumption, since we believe that education is correlated with more civic-minded choices that induce people to adopt more conservation behaviour. What follows is the discussion of our result.

Tables 1.7 to 1.10 show the results obtained from estimation of equation (1.1) when we transformed the model to a log-log model (Table 1.8) and when we restricted the data to the summer months (Tables 1.9 and 1.10). Tables 1.13 and 1.14 represent the results when estimating equation (1.2) using the whole dataset and the dataset limited to the summer months, respectively. The next part of this section analyses the results obtained from the multilevel regressions. Tables 1.15 and 1.16 illustrate the results of estimating equations (1.4) and (1.5). The first columns in Tables 1.7 to 1.14 (except Tables 1.11 and 1.12) show the results of the regression (equations (1.1), (1.2)) in isolation from any dummy variables. In the next columns, we add city (municipality), CT, year and month, or a combination of the dummies.

The results from Table 1.7 - Panel A show that, whenever significant, the coefficients of education variables are both negative. Since these coefficients are in reported percentage and the omitted category is high school, we interpret them relative to the population in each CT with a high-school diploma/degree. The results suggest that, holding the population of people who have a post-secondary degree constant, a one percentage point decrease in the population of individuals who have no certificate (which translates into a one percentage point increase in the population of people who have high school degree) in each CT, can increase the monthly water consumption per square footage. On the other hand, holding all other variables constant, a one percentage point increase in the population of people who have a post-secondary education relative to a high school degree in each CT will decrease household monthly water consumption per square foot.

In addition to education, other variables that are considered in these regressions, such as average income in each DA and average monthly temperature, emerge as significant predictors of household monthly water consumption. The results suggest that a 1000$ increase in the average income of people living in the same DA decreases household monthly water use by an average 0.0012 $m^3/sqft$. Furthermore, a 1°C increase in average monthly temperature increases monthly water consumption by an average 0.0002 $m^3/sqft$. Based on the result shown in Table 1.7, the coefficient of average income no-certificate and average temperature keep almost the same level of magnitude and remain statistically significant at the 1% level through all other model specifications (column 2 to 5). In regression 2, we controlled for the municipalities fixed effects. Except for education, the coefficients of other variables did not change significantly. Interestingly, the magnitude of both education coefficients increased. Also, post-secondary variable is shown to be at a higher significance level when compared to the basic model.

In regression 3, we have added the CT fixed effects to the underlying model. There is a significant difference between the results. The coefficient of education has gone up remarkably. This suggests that when controlling for CT fixed effects, a one percentage point increase in the population of people who have the post-secondary degree would decrease monthly water consumption, on average by 0.0149 $m^3/sqft$. On the other hand, the coefficient of no-certificate suggests that a one percentage point decrease in the population of people who have no certificate would increase monthly water consumption by an average 0.0403 $m^3/sqft$. The effects of average income and temperature on household water consumption are similar to those obtained previously.

The improved Adjusted-R^2, which penalizes the model for adding extra variables (CT dummy variables in this case), is worth noting. The adjusted-R^2 increases from 0.0017 to 0.14. This shows that the predictive ability of the proposed model increases when we control for CT fixed effects. Regression 4 and 5 represent the results of the OLS estimation when we control for year and month fixed effects. The results are very similar to the underlying model and only the magnitude of climate variables changed. This is somewhat predictable, as each year and month has a different weather condition.

Turning now to the second part of this table, what follows is a description of the result from the OLS estimation when cluster-adjusted standard errors are considered. Table 1.7 - Panel B, presents the result obtained from the estimation of equation (1.1), with clustered standard errors at CT and DA levels. Except the income coefficient, which is statistically significant in all regressions, other variables are consistent in magnitude but inconsistent in statistical level of significance. Interestingly, as we change the clustering from CT to DA and further to house level (Reg (5 and 6)), the adjuster-R^2 increases from 0.0017 to 0.1486 in both regressions. It is also interesting to note that the magnitude of the coefficients does not change when we cluster standard errors at the DA and house level. However, as the standard errors are increasing by an increasing number of clusters (from DA to house), the coefficient of no-certificate turns out to be not statistically significant.

Table 1.8 contains estimates of a log-log specification, where all (except climate variables) are in natural logarithms. We ignored the consideration of CT dummies (and clustering standard errors at DA and house levels), as it turns out that the independent variables become highly correlated and are eventually omitted from the regressions. In Panel A, standard errors are robust. In Panel B, they are clustered at the CT level.

Results from Table1.8 - Panel A suggest that whenever significant, the coefficients of education levels are negative and similar in magnitude. A one percent increase in population of people who have a post-secondary degree decreases monthly water consumption by 0.11% (Reg (1, 3, and 4)) and a one percent decrease in population of people who have no certificate in each CT results on a 0.05% increase in monthly water consumption (Reg (2)). On the other hand, in all model specification income coefficient is statistically significant at least at 10% level and always negative. The magnitude of all coefficients change when we control for city fixed effects (Reg (2)). For the income coefficient, these results suggest that that a one percent increase in the average income of households at DA, results in an average 0.19% decrease in household monthly water consumption. When we cluster standard errors, the coefficient on income stays statistically significant and similar in magnitude to the results shown in Panel A. On the other hand, coefficients of education are similar in magnitude but not statistically significant in all regressions.

Tables 1.9 and 1.10 summarize the results of running equation 1.1 when we restrict the sample to summer months. The results presented in these two tables are very similar to the results shown in Tables 1.7 and 1.8 in terms of sign of the coefficients. However, the magnitude of the coefficients increases slightly in Tables 1.9 and 1.10, with the exception of the income coefficient. When we consider the effect of average income on monthly water consumption in summer, the coefficient of income decreases in absolute value, from 0.26 to 0.14 in log-log model (Tables 1.8 and 1.10). On the other hand, although the coefficients of average temperature do not vary a lot in terms of magnitude and statistical significance, the coefficients of average precipitation become statistically significant. This is not surprising; in the hot summer months, water consumption is higher than other months and water is highly needed. Therefore, it is to be expected that the change in income would not change the summertime water demand as it would in other months.

Overall, the results from running the regression 1.1 indicate that all variables considered in the OLS and log-log model strongly affect monthly water consumption, both during the year and in summer months. In the next step, a Ramsey RESET test is performed. The result of the test is shown in Table 1.11 when all months are considered, and 1.12 when only summer months are analyzed. Following the result of Ramsey RESET test, we decided to estimate equation 1.2, in which squared values of independent variables are added. The results are reported in Table 1.13 and Table 1.14 when we limit the analysis to the summer months.

Table 1.13 summarizes the results of running regression 1.2 on all months of 2012 to 2014. In this setting, the coefficients of average income and no-certificate are significant in all columns, however, the coefficient of post-secondary is only significant when we control for city fixed effects (Reg (2)). In this regard, we focus on interpreting the coefficients that are reported in the second column of Table 1.13.

Taking the derivative with respect to $AvgInc_{jkl}$ yields:

$$\frac{\delta C_{ijkl}}{\delta AvgInc_{jkl}} = -0.01 + 2 * 0.00007 * AvgInc_{jkl}$$

Solving for the $AvgInc_{jkl}$:

$$\frac{\delta C_{ijkl}}{\delta AvgInc_{jkl}} = 0 \Rightarrow \text{AvgInc}_{jkl}=70$$

This result suggests that the relationship between the average income of people in a DA and household monthly water consumption is convex. The average water consumption in a DA goes down with increasing average income of people in a DA, and then starts to go up when the average income reaches to $70,000$\$.

We can calculate the effect of educational attainment on water consumption in a similar way:

Taking the derivative with respect to $PostSecondary_{jkl}$ yields:

$$\frac{\delta C_{ijkl}}{\delta PostSecondary_{jkl}} = -0.027 + 2 * 0.0002 * PostSecondary_{jkl}$$

Solving for the $PostSecondary_{jkl}$:

$$\frac{\delta C_{ijkl}}{\delta PostSecondary_{jkl}} = 0 \Rightarrow \text{PostSecondary}_{jkl}\text{=}67.5$$

Therefore, the average water consumption in a CT goes down as the population of people who have post-secondary education increases and then it starts to increase when the population reaches to 67.5%

Taking derivative with respect to $NoCertificate_{jkl}$ yields:

$$\frac{\delta C_{ijkl}}{\delta NoCertificate_{jkl}} = 0.00074 - 2 * 0.0001 * NoCertificate_{jkl}$$

Solving for the $NoCertificate_{jkl}$:

$$\frac{\delta C_{ijkl}}{\delta NoCertificate_{jkl}} = 0 \Rightarrow \text{NoCertificate}_{jkl}\text{=}3.7$$

This result suggests that the average monthly water consumption decreases as the population of people who have no certificate increases in a CT. However, there is a turning point (3.4%) where the effect reverses.

The average marginal effect of average income on water consumption is β_1+$2\beta_2\overline{AvgInc_{jkl}}$. With $\overline{AvgInc_{jkl}} = 49.0254$, the marginal effect of post-secondary education on water consumption is -0.0065. Therefore, at the average level of income (49.0254), a 1000\$ increase in the average income reduces water consumption by 0.0065 $m^3/sqft$ in each DA.

In a similar way, we can calculate the average marginal effect of the population with no certificate (post-secondary) on water consumption. With the $\overline{NoCertificate_{jkl}}$= 16.63

($\overline{PostSecondary_{jkl}}$= 57.98), the marginal effect is -0.0025 (-0.025). This suggests that on average, an additional 1% decrease (increase) in population of people who have no certificate (post-secondary education) would increase (decrease) monthly water consumption by 0.004 (0.025) $m^3/sqft$. Interestingly, the result from the average marginal effect of education on monthly water consumption suggests that as the population of people with higher educational attainment increases in each CT, people tend to consume less water. This differs from the result of equation 1.1 (Tables 1.7 to 1.10), where moving from no-certificate to high school certificate increases water consumption, whereas moving from high school to post-secondary decreases monthly water consumption.

Table 1.14 shows the result of running regression 1.2 when the sample is restricted to summer months. The results are similar in terms of magnitude, sign and level of significance. Since the right-hand-side variables are time-invariant, the values for the $\overline{AvgInc_{jkl}}$, $\overline{PostSecondary_{jkl}}$ and $\overline{NoCertificate_{jkl}}$ are the same as before; therefore, the marginal effect has the same magnitude and interpretation.

The final part of this section discusses the results when the hierarchical nature of the data is considered. More specifically, instead of the usual fixed-effect model, we allow for different intercepts for municipalities and CTs. The result is shown in Table 1.15 when we considered the monthly consumption of each household, and in Table 1.16 when we averaged the household monthly water consumption. The right side in both tables shown the results when we restricted the sample to summer months.

The first column in Tables 1.15 and 1.16 presents the result from estimating equations 1.4 and 1.6 (Reg (1)). The second column shows the results of a two-level (City and CT) mixed model (equations 1.5 and 1.7). The general trend that can be seen is that introducing more hierarchical levels to the model results in the coefficients of education increasing in absolute value and the coefficient of average income decreasing. In what follows, we will discuss the two parts of the model in more detail.

The upper section of Table 1.15 shows the fixed-effects part of the model. The result obtained from this section is similar to the result in previous parts. A one percentage point increase in the population of people who have a post-secondary degree will result in an average 0.0043 and 0.0037 $m^3/sqft$ decrease of water consumption each month when the one-level and two-level geographical division is considered, respectively. Moreover, a one thousand dollar increase in average income of people who live in the same DA would result in lower water consumption; by contrast, as temperature increases, people would consume more water. Most of the coefficients in the fixed-effects part of the model emerged as highly significant, similar to the previous results. Interestingly, in these results, the magnitude of both education variables and average income do not vary when summer months are considered.

Random Part in Tables 1.15 and 1.16 reflects the results of considering different intercepts in the model. In both tables, the results in each column imply different intercepts, one for each city (Reg (1)) and 91 intercepts for each CT (Reg (2)). However, intercepts are not directly estimated. What is reported in Tables 1.15 and 1.16 is the estimated standard deviation of those random intercepts along with their standard errors. Since the estimated standard deviations are greatly different from 0 and statistically significant, we can conclude that these intercepts do change from city to city and from CT to CT. In addition, when comparing the random intercepts to the metrics of the dependent variable ($m^3/sqft$), it seems that these values are substantial. Moreover, the likelihood-ratio test rejects the null hypothesis of linear regression model with fixed-effects against the multi-level model and confirms that this random intercept model offers significant improvement over the linear regression with fixed effects only, which further indicates the statistical importance of considering the levels.

On the other hand, to compare the suitability of the one-level versus two-level model (comparing Reg (1) and Reg (2)), we run another precise LR test. This LR test performs a test for whether the two-level model fits significantly better than one-level model. The result of the LR test is shown in below each part of the tables. Model A and B refers to Reg (1) and (2) in each part. It turned out that the two-level model in all cases brought great improvements to the model ($P = 0.000$).

1.6 Conclusion

The present study makes several noteworthy contributions to the literature by creating a unique dataset that matches household level data to the local characteristics at different geographical levels. To the best of our knowledge, there are very few studies that focus on the effects of local features on household decisions. The present study provides additional evidence with respect to the constructed dataset, confirming the impacts of local characteristics on household water consumption decisions. In particular, this study set out to evaluate the effects of education and average income at the local level on water consumption in the Tri-Cities of Cambridge, Kitchener and Waterloo. Multiple regression analysis shows that within each group of people who are living in the same area, the level of education could be one of the strong predictors of water consumption. Other predictors, such as average income and temperature, are also revealed to have significant effects on household monthly water consumption.

Interestingly, although the results show that education affects household water consumption, there were differences in how increasing levels of education affects water use. In particular, increasing educational attainment at lower levels of education (from no certificate to high school certificate) increases water consumption, but the effect reverses when people receive post-secondary education. These relationships may partly be explained by how people make their choices when they become more educated. For example, higher-educated people might start to value water more than they did before. Also, individuals with higher education might start using more water-efficient appliances that not only save more water, but also save more money in the long run. On the other hand, adults who move from the No Certificate to the High School bracket of education might start to value hygiene more than they did before and care less about the amount of water they use. For example, they might take more showers or use their washing machines more for sanitation purposes.

It is interesting to note that in both cases, there exists a turning point where the relationship changes. For example, the results suggest that the average water consumption will decrease as the population of people with post-secondary education increases in each

CT; however, the relationship reverses when around more than 67.5% of the population in CT are people with post-secondary education. A possible explanation for this could relate to local features of the neighborhoods in which highly-educated people prefer to live. For example, larger houses and greener gardens, which essentially imply a high amount of water consumption, are owned by people in higher income brackets. On the other hand, higher income is usually associated with higher education.

Moreover, the result from the Multilevel Mixed Effect regression suggests that the effect of education on water consumption differs from one region to another. The education level of people who live close to each other (i.e., in a smaller geographic area) affects the average water consumption of that group of people more than it could affect a distant group. This result suggests that there should be more awareness at the smaller community levels about household water consumption and conservation. Since the study was limited to each CT and we did not have the information on adjacent houses, it was not possible to look at the peer behaviour in smaller geographical divisions. Therefore, a future study investigating the effects of peer behaviour would be of interest.

Taken together, the findings of this study suggest a role for the government in promoting higher education in the Region of Waterloo. Although the government is unable to relocate people to harmonize neighborhood levels of education, it can invest in the educational system of each neighborhood. Ensuring appropriate systems, services and support for higher education should be a priority for decreasing water consumption in the region. Furthermore, the higher water usage among people with a high school degree may be a reason to educate individuals about the benefits of conserving water. For example, promoting a culture of water conservation could start at the high school level. It is also necessary to investigate why such an increase occurs and how individuals use that extra amount of water.

On the other hand, a turning point after which the consumption of water increases in areas with more educated people can direct the government to plan for substantial water saving in that neighborhood. Since these households are already highly educated, tailoring a different policy approach such as an increasing block pricing scheme would best curb their water demands. There is, therefore, a definite need to design and adopt a unique policy for each neighborhood based on their underlying characteristics.

The findings of this research show that education plays a more significant role in water consumption during summer months, whereas the effect of average income decreases slightly. These results suggest that local governments should more strongly emphasise promoting water conservation by implementing water efficiency plans that manage household consumption during summer months.

The study is limited by the lack of information at the household level. Educational attainment and average income variables are reported at different geographical levels. Further research is required to determine whether the observed relationship between explanatory variables (educational attainment and average income) and water consumption would exist if the data was aggregated from the household-level dataset. In addition, we work on water consumption data from 2012 to 2014, using static right-hand-side variables from Statistics Canada Census data 2011 (the most recent census data);, therefore, we are unaware of any mobility issues that might have changed the distribution of people at the considered geographical levels.

1.7 Tables

Table 1.1: Studies on the water consumption and water conservation outside Canada.

Author	Place	Term	Data	Dep. Var	Indep. Var	Method	Main Findings	Critique
Renwick and Archibald [1998]	Santa Barbara Goleta (California, United States)	1985 -1990	119 Household	Monthly water consumption	Income level	2SLS[1]	Smaller household are more sensitive to water price changes.	Small sample
De Oliver [1999]	San Diego -Texas	July 1995 - March 1997	203 Census Tracts	-	-	-	Positive relationship between conservation and both higher income and education.	Small sample No econometric method used to confirm the findings. Findings are based on data summary statistics
Syme et al. [2004]	Perth (Western Australia)	July 1998 - September 2000	397 Households	Monthly outdoor water consumption in summer	Garden Interest Income Dummies	Structural Equation Model	Higher Income households used more water.	Short Time- Scale Small sample
Arbués et al. [2010]	Zaragoza City (Spain)	1996 - 1998	1500 Households	Daily water consumption	Wealth index Climate weather	Dynamic panel data	Positive relationship between water consumption and property value.	Short Time- Scale Small sample
Fielding et al. [2012]	South-east Queensland (Australia)	October 2009 - March 2010	1008 Households	Monthly water consumption	Psychological Var. Household annual gross Income Age Level of education	Sequential regression analysis	Households with more people and higher income used more water.	Short Time- Scale Small sample
Jorgensen et al. [2013]	South Australia Victorian (Australia)	2009-2010	615 Households	Monthly water consumption	Household size Attitued toward water pricing Conservation commitment	LGC[2]	Household size is significant predictor of water consumption.	Small sample

1. Two Stage Least Square
2. Latent Growth Curve model

Table 1.2: Studies on the water consumption and water conservation inside Canada.

Author	Location	Term	Sample Size	Dep. Var	Indep. Var	Method	Main Findings	Critique
Aydinalp et al. [2004]	All Canadian provinces	1993	2749 Households	DHW[1] SH[2]	1. DWH Heating system characteristics 2. Socio-demographic characteristics of household:income dwelling ownership	NN[3]	Both DHW and SH increase linearly as income increases.	Small sample for Canada. Short time-scale
Olmstead et al. [2003]	United States and Canada (Including Waterloo - Cambridge)	1998 (Two periods of two weeks)	1082 Households	Daily water consumption	1. Gross annual household income 2. Family size 3. Home age	GLS[4] DDC[5] IV[6]	1. Different price structure induce different water demand . 2. Positive income elasticity.	Small sample for Canada. Short time-scale
Fullerton Jr et al. [2013]	Halifax	1996 -2009	52 Observations	Quarterly municipal water consumption per customer	1. Price 2. Weather Var. 3. Non-seasonally adjusted employment,	OLS[7] 2SLS[8]	Consumption is price inelastic.	1. Small sample size 2. Only metered water is considered 3. Lack of Socio-demographic independent var.
Dupont and Renzetti [2013]	All Canadian provinces	2006	9479 Households	Monthly water consumption	1. Climate Var. 2. Price 3. Non-Price conservation policy var. 4. Household income	Probit	Price affects the indoor water use more than outdoor water use decisions.	Small sample

1. Domestic Hot Water
2. Space Heating
3. Neural Network
4. General Least Square
5. Discrete-Continuous Choice
6. Instrumental Variables
7. Ordinary Least Square
8. Two Stage Least Square

Table 1.3: Summary of the underlying characteristics of the Tri-cities

	Educational Attainment				
	University degree/certificate	Collage diploma	High-School diploma	No certificate	Population[1]
Cambridge	18.1%	33.6%	28.4%	19.8%	83690
Kitchener	25.3%	31.8%	26.2%	16.6%	147430
Waterloo	46.6%	24.9%	19%	9.5%	63780
		Income Composition		**Labour Force Status** [5]	
	Median employment income[2]	Top 5%[3]	Top 1%[4]	Employment rate	Unemployment rate
Cambridge	\$48,001	3.9%	0.5%	63.8%	8.3%
Kitchener	\$47,248	3.7%	0.6%	64.8%	7.1%
Waterloo	\$59,155	8.1%	1.6%	63.7%	7.2%

Source: Statistics Canada - National Household Survey(NHS)
1. Population aged 25 years and over.
2. Median employment income of those persons worked full-year, full-time: worked 49 to 52 weeks.
3. percentage of the population aged 15 years and over who had total income that put them in the top five percent in 2011 (compared with 5% in Canada).
4. percentage of the population aged 15 years and over who had total income that put them in the top one percent in 2011 (compared with 1% in Canada).
5. Based on total labour force in May 2011.

Table 1.4: House Distribution in Tri-Cities - (2012-2014)

Municipality	Freq.	Percent	Cum.
Cambridge	6,412	29.47	29.47
Kitchener	7,892	36.28	65.75
Waterloo	7,452	34.25	100
Total	21,756	100	

Source: authors' own calculation.

Table 1.5: Summary Statistics (2012-2014)

Variable	Observation	Mean	Std. Dev.	Min	Max
Avg. Total Consumption (m^3)	21756	36.0515	80.5165	1	7423.759
Avg. Income ($1000\$/year$)	21756	49.0254	12.03	17.025	97.376
Post-Secondary (%)	21756	57.9863	9.1705	28.9398	70.2531
No-Certificate (%)	21756	16.6302	5.2002	9.3354	43.553
High-School (%)	21756	25.3696	4.8519	17.4757	38.6059
Square Footage	21756	1389.779	1877.357	10	133692

Source: authors' own calculation.

Table 1.6: Summary Statistics for Water Consumption of 106571 Houses (2012-2014)

	Observation	Mean	Std. Dev.	Min	Max
All houses in the dataset:					
Avg. Total Consumption (m^3)	106571	236.8038	775.1275	0.6666	62234.61
Houses with consumption > 7423.759 :					
Avg. Total Consumption (m^3)	204	14379.26	8236.537	7440	62234.61
Houses with consumption < 1 :					
Avg. Total Consumption (m^3)	2	0.8	0.1885	0.6666	0.9333

Source: Authors' own calculation.

Table 1.7: OLS estimates of the effects of educational attainment and average income on average monthly water consumption - (2012-2014)

Panel A: Robust S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)	Reg(5)	
Independent Variables:						
Avg_Inc (1000$)	-0.0012***	-0.0011 ***	-0.0004***	-0.0012***	-0.0012***	
	(0.00008)	(0.00008)	(0.00003)	(0.00008)	(0.00008)	
Post_Secondary (%)	-0.0001	-0.0043***	0.0149*	-0.0001	-0.0001	
	(0.0001)	(0.0003)	(0.0077)	(0.0001)	(0.0001)	
No_Certificate (%)	-0.0012***	-0.0037***	0.0403***	-0.0012***	-0.0012***	
	(0.0002)	(0.0004)	(0.0079)	(0.0002)	(0.0002)	
Avg. Temp (°C)	0.0002***	0.0002***	0.0002***	0.0002***	-0.00001	
	(0.00007)	(0.00007)	(0.00006)	(0.00007)	(0.0002)	
Avg. Precip (mm)	-0.0006	-0.0006	-0.0006	-0.0003	-0.0011	
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0008)	
City Fixed Effect	NO	YES	NO	NO	NO	
CT Fixed Effect	NO	NO	YES	NO	NO	
Year Fixed Effect	NO	NO	NO	YES	NO	
Month Fixed Effect	NO	NO	NO	NO	YES	
Constant	0.1317 ***	0.4455***	-1.3186**	0.1308***	0.1321***	
	(0.0152)	(0.035)	(0.5389)	(0.0152)	(0.0153)	
Adjusted-R^2	0.0017	0.0043	0.1486	0.0017	0.0017	
Panel B: Cluster S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)	Reg(5)	Reg(6)
Independent Variables:	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (DA)	Cluster (House)
Avg_Inc (1000$)	-0.0012**	-0.0011*	-0.0012**	-0.0012**	-0.0004**	-0.0004***
	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0002)	(0.0001)
Post_Secondary (%)	-0.0001	-0.0043*	-0.0001	-0.0001	0.0149	0.0149
	(0.001)	(0.0025)	(0.001)	(0.001)	(0.0173)	(0.0320)
No_Certificate (%)	-0.0012	-0.0037	-0.0012	-0.0012	0.0403***	0.0403
	(0.0019)	(0.0027)	(0.0019)	(0.0019)	(0.0049)	(0.0324)
Avg. Temp (°C)	0.0002***	0.0002***	0.0002***	-0.00001	-0.00001	-0.00001
	(0.00004)	(0.00004)	(0.00004)	(0.0001)	(0.00009)	(0.00009)
Avg. Precip (mm)	-0.0006***	-0.0006***	-0.0003	-0.0011***	-0.0011	-0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
City Fixed Effect	NO	YES	NO	NO	NO	NO
CT Fixed Effect	NA	NA	NA	NA	YES	YES
Year Fixed Effect	NO	NO	YES	NO	NO	NO
Month Fixed Effect	NO	NO	NO	YES	YES	YES
Constant	0.1317	0.4455**	0.1308	0.1321	-1.3182	-1.3182
	(0.0996)	(0.2144)	(0.0994)	(0.0997)	(1.056523)	(2.2142)
Adjusted-R^2	0.0017	0.0043	0.0017	0.0017	0.1486	0.1486
Observation	391608	391608	391608	391608	391608	391608

Note: The omitted category for educational level is “High School.” Standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.8: OLS estimates (log-log model) of the effects of educational attainment and average income on average monthly water consumption - (2012-2014)

Panel A: Robust S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)
Avg_Inc (1000$)	-0.2613***	-0.1933***	-0.2613***	-0.2613***
	(0.0190)	(0.0199)	(0.019)	(0.019)
Post_Secondary (%)	-0.1125***	0.0016	-0.1125***	-0.1125***
	(0.0413)	(0.047)	(0.0413)	(0.0413)
No_Certificate (%)	0.0144	-0.0587**	0.0144	0.0144
	(0.026)	(0.0262)	(0.0260)	(0.026)
Avg. Temp (°C)	0.0088***	0.0088***	0.0103***	-0.0296***
	(0.0003)	(0.0003)	(0.0003)	(0.0017)
Avg. Precip (mm)	0.0004	0.0004	-0.0124***	-0.0198***
	(0.0028)	(0.0028)	(0.0029)	(0.004)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	-2.5392***	-3.1869**	-2.4852***	-2.4974***
	(0.2414)	(0.2588)	(0.2411)	(0.2414)
Adjusted-R^2	0.0039	0.0062	0.0043	0.0062
Panel B: Cluster S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)
Independent Variables:	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (CT)
Avg_Inc (1000$)	-0.2613657**	-0.1933*	-0.2613**	-0.2613**
	(0.1196)	(0.11)	(0.1196)	(0.1196)
Post_Secondary (%)	-0.1125	0.0016	-0.1125	-0.1125
	(0.3347)	(0.4528)	(0.3347)	(0.3347)
No_Certificate (%)	0.0144	-0.0587	0.0144	0.0144
	(0.2055)	(0.2267)	(0.2055)	(0.2055)
Avg. Temp (°C)	0.0088***	0.0088***	0.0103***	-0.0296
	(0.0022)	(0.0022)	(0.0035)	(0.0249)
Avg. Precip (mm)	0.0004	0.0004	-0.0124***	-0.0198***
	(0.0148)	(0.0148)	(0.0038)	(0.0070)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	-2.5392	-3.1869	-2.4852	-2.4974
	(1.832)	(2.4003)	(1.8196)	(1.8243)
Adjusted-R^2	.0039	0.0062	0.0043	0.0062
Observation	391608	391608	391608	391608

Note: The omitted category for educational level is "High School." Standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.9: OLS estimates of the effects of educational attainment and average income on average monthly water consumption - (2012-2014 - summer months)

Panel A: Robust S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)	Reg(5)
Avg_Inc (1000$)	-0.0012***	-0.0010***	-0.0004***	-0.0012***	-0.0012***
	(0.0001)	(0.0001)	(0.00006)	(0.0001)	(0.0001)
Post_Secondary (%)	-0.0004*	-0.0046***	0.0232	-0.0004*	-0.0004*
	(0.0002)	(0.0007)	(34.2757)	(0.0002)	(0.0002)
No_Certificate (%)	-0.0015***	-0.0041***	0.0340	-0.0015***	-0.0015***
	(0.0005)	(0.0008)	(9.7130)	(0.0005)	(0.0005)
Avg. Temp (°C)	0.0006	0.0006	0.0006	0.0002	0.0021
	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0013)
Avg. Precip (mm)	-0.0011	-0.0011	-0.0011	-0.0004	-0.00007
	(0.0009)	(0.0009)	(0.0008)	(0.0011)	(0.0012)
City Fixed Effect	NO	YES	NO	NO	NO
CT Fixed Effect	NO	NO	YES	NO	NO
Year Fixed Effect	NO	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	NO	YES
Constant	0.1457***	0.4609***	-1.7228	0.1493***	0.1129***
	(0.0285)	(0.0661)	(2226.048)	(0.0289)	(0.0382)
Adjusted-R^2	0.0015	0.0038	0.1381	0.0015	0.0015
Panel B: Cluster S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)	Reg(5)
	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (DA)
Avg_Inc (1000$)	-0.0012*	-0.0010*	-0.0012*	-0.0012*	-0.0004**
	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0002)
Post_Secondary (%)	-0.0004	-0.0046*	-0.0004	-0.0004	0.0232
	(0.001)	(0.0026)	(0.001)	(0.001)	(44.0513)
No_Certificate (%)	-0.0015	-0.0041	-0.0015	-0.0015	0.0340
	(0.002)	(0.0029)	(0.002)	(0.002)	(15.2206)
Avg. Temp (°C)	0.0006***	0.0006***	0.0002	0.0021***	0.0021***
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0003)
Avg. Precip (mm)	-0.0011***	-0.0011***	-0.0004*	-0.00007	-0.00007
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
City Fixed Effect	NO	YES	NO	NO	NO
CT Fixed Effect	NA	NA	NA	NA	YES
Year Fixed Effect	NO	NO	YES	NO	NO
Month Fixed Effect	NO	NO	NO	YES	YES
Constant	0.1457	0.4609**	0.1493	0.1129	-1.7556
	(0.1030)	(0.2299)	(0.1032)	(0.1024)	(3458)
Adjusted-R^2	0.0015	0.0038	0.0015	0.0015	0.1381
Observation	130536	130536	130536	130536	130536

Note: The omitted category for educational level is “High School.” Standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.10: OLS estimates (log-log model) of the effects of educational attainment and average income on average monthly water consumption - (2012-2014 - summer months)

Panel A: Robust S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)
Avg_Inc (1000$)	-0.1475***	-0.0599*	-0.1475***	-0.1475***
	(0.0296)	(0.031)	(0.0296)	(0.0296)
Post_Secondary (%)	-0.4865***	-0.4898***	-0.4865***	-0.4865***
	(0.0756)	(0.0816)	(0.0756)	(0.0756)
No_Certificate (%)	-0.0897*	-0.1808***	-0.0897*	-0.0897*
	(0.0462)	(0.0467)	(0.0462)	(0.0462)
Avg. Temp (°C)	0.0088***	0.0088***	0.0018	0.0373***
	(0.0024)	(0.0024)	(0.0028)	(0.0062)
Avg. Precip (mm)	-0.0248***	-0.0248***	-0.0143**	-0.0041
	(0.0045)	(0.0044)	(0.0055)	(0.0057)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	-1.0979**	-1.2857	-1.0332**	-1.7144***
	(0.4351)	(0.4507)	(0.4353)	(0.4511)
Adjusted-R^2	0.0027	0.0058	0.0029	0.0029
Panel B: Cluster S.E.	Reg(1)	Reg(2)	Reg(3)	Reg(4)
	Cluster (CT)	Cluster (CT)	Cluster (CT)	Cluster (CT)
Avg_Inc (1000$)	-0.1475	-0.0599	-0.1475	-0.1475
	(0.1155)	(0.097)	(0.1155)	(0.1155)
Post_Secondary (%)	-0.4865	-0.4898	-0.4865	-0.4865
	(0.4233)	(0.3531)	(0.4233)	(0.4233)
No_Certificate (%)	-0.0897	-0.1808	-0.0897	-0.0897
	(0.2459)	(0.2072)	(0.2459)	(0.2459)
Avg. Temp (°C)	0.0088**	0.0088**	0.0018	0.0373***
	(0.0044)	(0.0044)	(0.0041)	(0.0137)
Avg. Precip (mm)	-0.0248***	-0.0248***	-0.0143**	-0.0041
	(0.0049)	(0.0049)	(0.0059)	(0.0091)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	-1.0979	-1.2857	-1.0332	-1.7144
	(2.2666)	(1.8416)	(2.2632)	(2.3227)
Adjusted-R^2	0.0027	0.0058	0.0029	0.0029
Observation	130536	130536	130536	130536

Note: The omitted category for educational level is "High School". Standard errors in parentheses. ***, **, * indicate significant level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.11: Ramsey RESET Test (2012-2014)

Ramsey RESET test using powers of the fitted values of monthly consumption
Ho: model has no omitted variables F(3, 391599) = 2382.68 Prob > F = 0.0000

Table 1.12: Ramsey RESET Test (2012-2014 - summer months)

Ramsey RESET test using powers of the fitted values of monthly consumption
Ho: model has no omitted variables F(3, 130527) = 860.88 Prob > F = 0.0000

Table 1.13: OLS estimates of the effects of educational attainment and average income on average monthly water consumption - (estimation with non-linear independent variables (2012-2014))

All Months	Reg(1)	Reg(2)	Reg(3)	Reg(4)
Avg_Inc (1000$)	-0.0116***	-0.01***	-0.0116***	-0.0116***
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
Avg_Inc^2	0.00008***	0.00007***	0.00008***	0.00008***
	(0.000007)	(0.000006)	(0.000007)	(0.000007)
Post_Secondary (%)	-0.001	-0.027***	-0.001	-0.001
	(0.0017)	(.0031273)	(0.0017)	(0.0017)
Post_Secondary^2	0.00001	0.0002***	0.00001	0.00001
	(0.0001)	(0.00002)	(0.00001)	(0.00001)
No_Certificate (%)	0.00038***	0.00074***	0.00038***	-0.00038***
	(0.0001)	(0.00011)	(0.0001)	(0.0001)
No_Certificate^2	-0.00002	-0.0001***	-0.00002	-0.00002
	(0.00002)	(0.00003)	(0.00002)	(0.00002)
Avg. Temp (°C)	0.0002***	0.0002***	0.0002***	-0.00001
	(0.00007)	(0.00006)	(0.00007)	(0.0002)
Avg. Precip (mm)	-0.0006	-0.0006	-0.0003	-0.0011
	(0.0005)	(0.0005)	(0.0006)	(0.0008)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	0.421***	0.0177	0.4201***	0.4214***
	(0.0679)	(0.0797)	(0.0678)	(0.0679)
Adjusted-R^2	0.0054	0.0082	0.0054	0.0053
Observation	391608	391608	391608	391608

Note: The omitted category for educational level is High School. Robust standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.14: OLS estimates of the effects of educational attainment and average income on average monthly water consumption - (estimation with non-linear independent variables (2012-2014 - summer months))

Summer Months	Reg(1)	Reg(2)	Reg(3)	Reg(4)
Avg_Inc (1000$)	-0.0117***	-0.01***	-0.0117***	-0.0117***
	(0.0017)	(0.0016)	(0.0017)	(0.0017)
Avg_Inc^2	0.00008***	0.00007***	0.00008***	0.00008***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Post_Secondary (%)	-0.0012	-0.0221***	-0.0012	-0.0012
	(0.0029)	(0.0055)	(0.0029)	(0.0029)
Post_Secondary^2	0.00001	0.0002***	0.00001	0.00001
	(0.00002)	(0.00005)	(0.00002)	(0.00002)
No_Certificate (%)	-0.00034*	-0.00071***	-0.00034 *	-0.00034*
	(0.00017)	(0.0002)	(0.00017)	(0.00017)
No_Certificate^2	0.00001	0.0001**	0.00001	0.00001
	(0.00004)	(0.00005)	(0.00004)	(0.00004)
Avg. Temp (°C)	0.0006	0.0006	0.0002	0.0021
	(0.0005)	(0.0005)	(0.0006)	(0.0013)
Avg. Precip (mm)	-0.0011	-0.0011	-0.0004	-0.00007
	(0.0009)	(0.0009)	(0.0011)	(0.0012)
City Fixed Effect	NO	YES	NO	NO
Year Fixed Effect	NO	NO	YES	NO
Month Fixed Effect	NO	NO	NO	YES
Constant	0.4144***	-0.0062	0.4180***	0.3816***
	(0.1154)	(0.1351)	(0.1155)	(0.1183)
Adjusted-R^2	0.0048	0.0075	0.0048	0.0048
Observation	130536	130536	130536	130536

Note: The omitted category for educational level is High School. Robust standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.15: Multilevel Mixed-Effect model estimation result

A:(2012-2014)			**B:Summer Months 2012-2014**		
Fixed Part:	Reg(1)	Reg(2)	Fixed Part:	Reg(1)	Reg(2)
Avg_Inc (1000$)	-0.0011***	-0.0004***	Avg_Inc (1000$)	-0.001***	-0.0004***
	(0.00005)	(0.00006)		(0.00009)	(0.0001)
Post_Secondary (%)	-0.0043***	-0.0279	Post_Secondary (%)	-0.0046***	-0.0306
	(0.0002)	(0.0208)		(0.0003)	(0.0209)
No_Certificate (%)	-0.0037***	-0.018	No_Certificate (%)	-0.0041***	-0.0217
	(0.0002)	(0.0277)		(0.0004)	(0.0278)
Avg. Temp (°C)	0.0002***	0.0002***	Avg. Temp (°C)	0.0006	0.0006
	(0.00006)	(0.00006)		(0.0005)	(0.0004)
Avg. Precip (mm)	-0.0006	-.000693	Avg. Precip (mm)	-0.0011	-0.0011
	(0.0005)	(0.0005)		(0.0009)	(0.0009)
Constant	0.4041***	2.0929	Constant	0.4174***	2.3049
	(0.0235)	(1.5993)		(0.0345)	(1.6079)
Random Part:			Random Part:		
Sd (City Residual)	0.0311***	0.2260***	Sd (City Residual)	0.031***	0.2364***
	(0.0127)	(0.1926)		(0.0127)	(0.1919)
Sd (Census_Tract Residual)		0.7308***	Sd (Census_Tract Residual)		0.7311***
		(0.0563)			(0.0565)
Observation	391608	391608	Observation	130536	130536
Groups:			Groups:		
City	3	3	City	0	3
Census Tract		91	Census Tract		91
LR test VS Linear Regression	978.51	61596.49	LR test VS Linear Regression	280.66	18551.80
	P(0.000)	P(0.000)		P(0.000)	P(0.000)
Log Likelihood	-125465.83	-95156.831	Log Likelihood	-49104.315	-39968.745
Likelihood-Ratio Test			**Likelihood-Ratio Test**		
Likelihood-Ratio Test	LR chi2(1) = 60617.99		Likelihood-Ratio Test	LR chi2(1) = 18271.14	
Assumption: A nested in B	Prob >chi2 = 0.000		Assumption: A nested in B	Prob >chi2 = 0.000	

Note: The omitted category for educational level is High School. Standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

Table 1.16: Multilevel Mixed-Effect model estimation result at household level

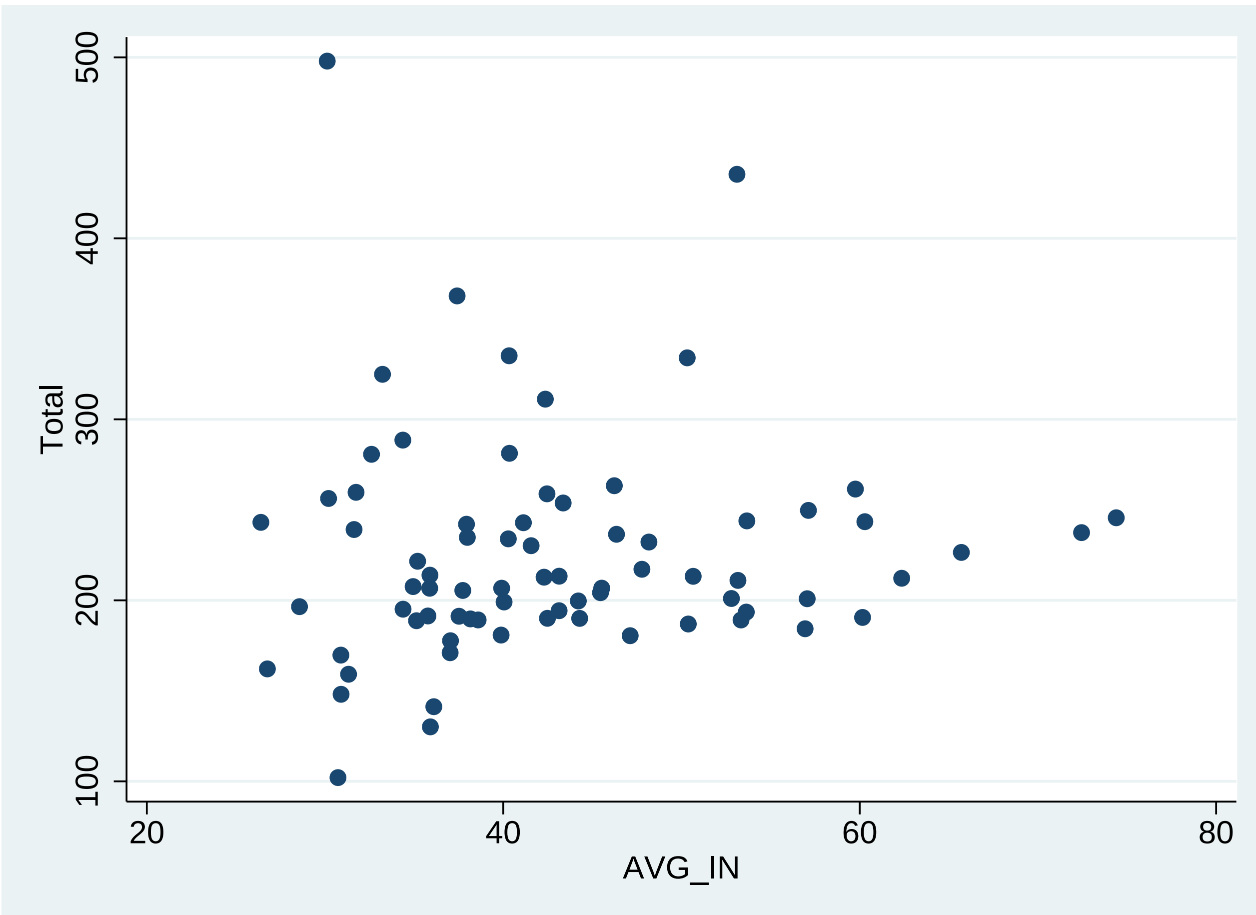
A: (2012-2014)			B: Summer Months 2012-2014		
Fixed Part:	Reg(1)	Reg(2)	**Fixed Part:**	Reg(1)	Reg(2)
Avg_Inc (1000$)	-0.0011***	-0.0005**	Avg_Inc (1000$)	-0.001***	-0.0005*
	(0.0002)	(0.0002)		(0.0002)	(0.0002)
Post_Secondary (%)	-0.0041***	-0.0283	Post_Secondary (%)	-0.0044***	-0.031
	(0.0008)	(0.0207)		(0.0008)	(0.0208)
No_Certificate (%)	-0.0036***	-0.0185	No_Certificate (%)	-0.0039***	-0.0221
	(0.0011)	(0.0275)		(0.0011)	(0.0276)
Constant	0.3911***	2.1246	Constant	0.4128***	2.3417
	(0.0641)	(1.5918)		(0.0684)	(1.6004)
Random Part:			**Random Part:**		
Sd (City Residual)	0.0297	0.2283	Sd (City Residual)	0.0296	0.2384
	(0.0128)	(0.1888)		(0.0129)	(0.1887)
Sd (Census_Tract Residual)		0.7173	Sd (Census_Tract Residual)		0.7177
		(0.0568)			(0.057)
Observation	21756	21756	Observation	21756	21756
Groups:			**Groups:**		
City	3	3	City	3	3
Census Tract		91	Census Tract		91
LR test VS Linear Regression	44.50	3174.29	LR test VS Linear Regression	37.36	2797.35
	P(0.000)	P(0.000)		P(0.000)	P(0.000)
Log Likelihood	-6157.3895	-4592.4948	Log Likelihood	-7701.2905	-6321.2975

Likelihood-Ratio Test		**Likelihood-Ratio Test**	
Likelihood-Ratio Test	LR chi2(1) = 3129.79	Likelihood-Ratio Test	LR chi2(1) = 2759.99
Assumption: A nested in B	Prob >chi2 = 0.000	Assumption: A nested in B	Prob >chi2 = 0.000

Note: The omitted category for educational level is High School. Standard errors in parentheses. ***, **, * indicate significance level at 1 percent, 5 percent, and 10 percent, respectively.

1.8 Figures

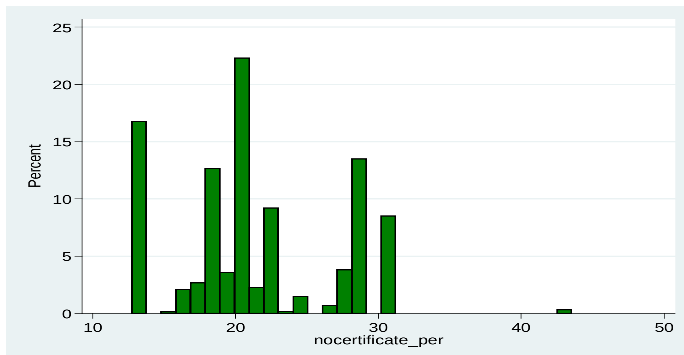
Figure 1.1: Distribution of Average Income at Census Tract Level



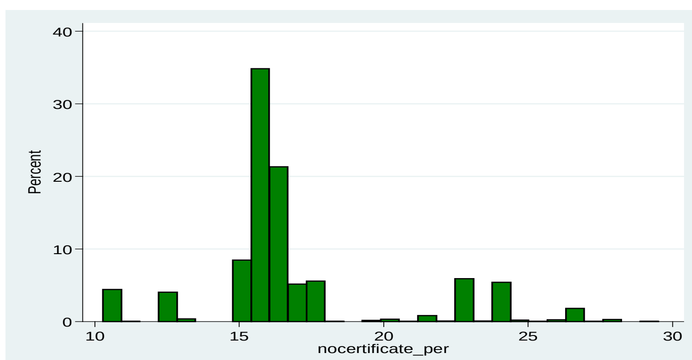
Source: Authors' own calculations

Figure 1.2: Distribution of percentage of people with No-Certificate in CTs of the Tri-Cities.
Source: Authors' own calculations

Cambridge:



Kitchener:



Waterloo:

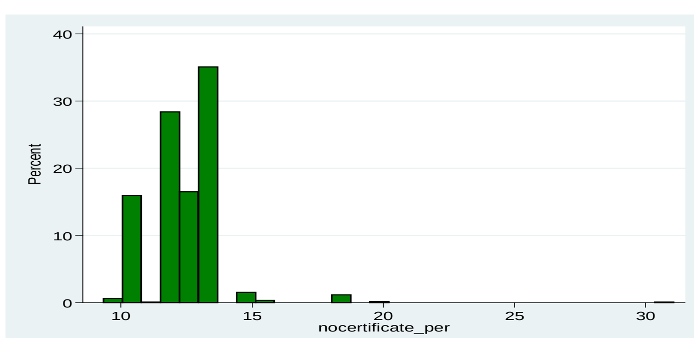
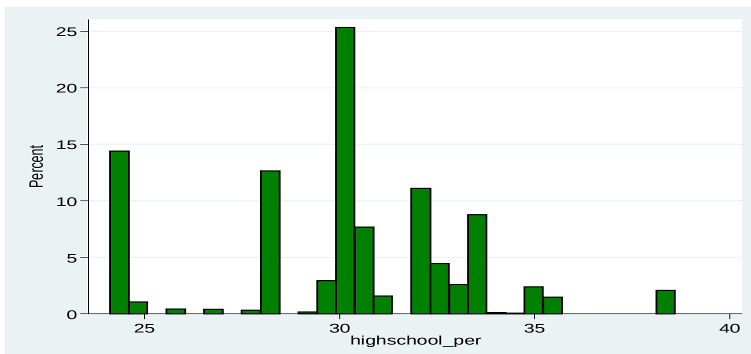
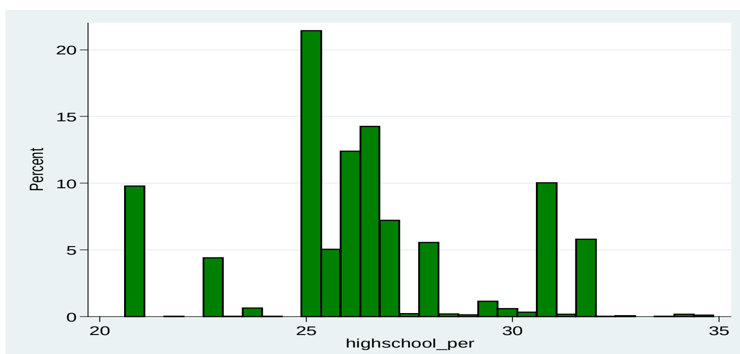


Figure 1.3: Distribution of percentage of people with High school degree in CTs of the Tri-Cities.
Source: Authors' own calculations

Cambridge:



Kitchener:



Waterloo:

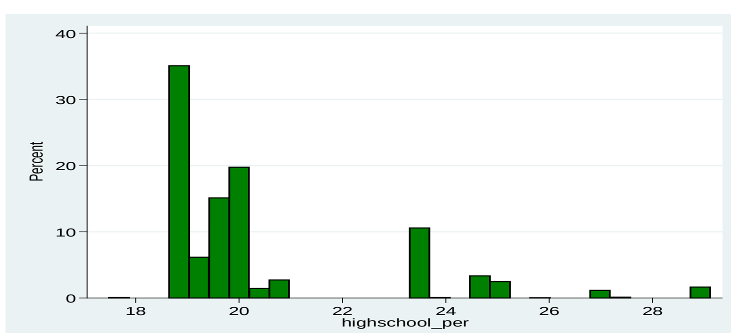
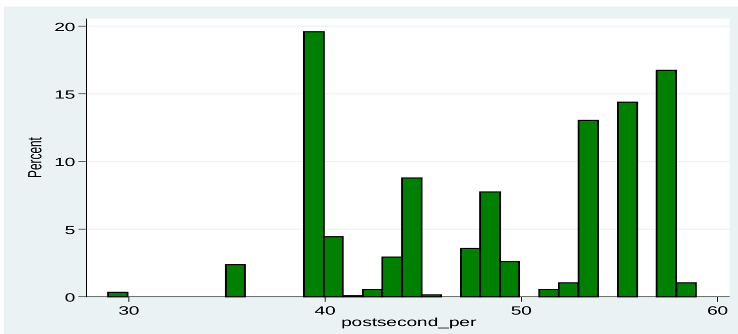
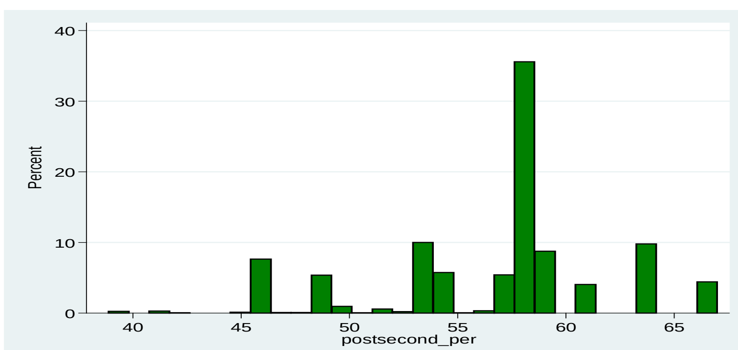


Figure 1.4: Distribution of percentage of people with Post-Secondary degree in CTs of the Tri-Cities.
Source: Authors' own calculations

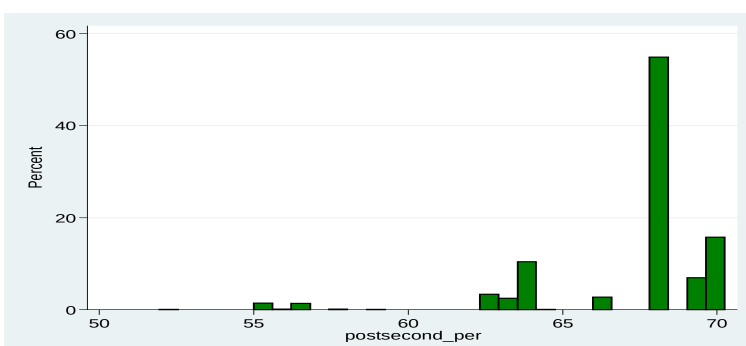
Cambridge:



Kitchener:



Waterloo:



Chapter 2

Estimating the Effects of Fuel Mix on the Hourly Ontario Energy Price (HOEP) & Global Adjustment (GA): Evidence from the Ontario Green Energy Act

2.1 Introduction

Electricity costs are an important location driver for many industries. Recent studies suggest that wholesale electricity prices in Ontario are higher than in other Canadian provinces as well as in many US jurisdictions. As pointed out by the Independent Electricity System Operator (IESO)[1], such high electricity rates have made Ontario's wholesale market unable to attract and support new entry business (IES). Other studies imply that Ontario

[1]The IESO manages the demand and supply in Ontario's electricity wholesale market on a second-by-second basis. For further information please visit http://www.ieso.ca/en/learn/about-the-ieso/what-we-do

is unable to compete with other jurisdictions both inside and outside of Canada (Sen [2015]). As a policy response, the Government of Ontario recently introduced a new hydro subsidy program. This hydro subsidy is equal to the provincial portion of the harmonized sales tax (HST), and therefore, it has been called an HST-rebate (The). Based on the HST-rebate program, consumers and some businesses would be exempt from paying the provincial portion of the Harmonized Sales Tax, which eases the burden of high electricity prices to some extent.

These policy responses as well as recent increases in electricity prices in Ontario motivate an empirical investigation into assessing the impacts of various factors that influence trends in electricity prices. This is particularly relevant given the enactment of the Ontario Green Energy Act (GEA) in 2009. A key mandate of the Act was to encourage increased electricity power generation from renewable sources of energy such as solar power, wind power, biofuels, and hydro power as well as the elimination of coal-fired plants[2]. This would be accomplished through subsidized contracts to generators based on renewable sources called Feed-in-Tariffs which guaranteed above-market wholesale rates for such generators over long time periods. Some studies acknowledge these fixed contracts to be a source of increasing electricity prices in Ontario (Wyman [2014], Sen [2015]).

The government at the time pointed to a variety of benefits that should result from the GEA including the creation of green economy jobs, reduced pollution levels consistent with emissions reductions under climate change targets, and improved health[3]. The elimination of coal-fired plants by Ontario was a particularly strong policy stance given the cheapness of coal as well as the fact that in 2008, it constituted 14.5% of electricity power generation [4].

[2] In addition, the government of Ontario in 2009 claimed that the GEA will create 50,000 new jobs over the coming years. For more details on the type of jobs please visit: https://www.thestar.com/business/2009/02/25/50000_green_jobs_a_tall_order.html

[3] For further details on pollution and health impacts please see Ontario Public Health Association (2002) (Perrotta [2002]), Harris et al. [2015] and Presentation to the Ontario Legislatures Standing Committee on General Government, Bill 9, Environmental Protection Act (Ending Coal for Cleaner Air Act), by the Ontario Public Health Association, available at, http://www.opha.on.ca/getmedia/3b13b10f-83a5-4f4e-912b-8f1c396c85e9/OPHA-Submission-Bill-9-Ending-Coal.pdf.aspx?ext=.pdf

[4] For further details on different types of energy sources in Ontario please refer to: http://www.ieso.ca/en/corporate-ieso/media/year-end-data/2008

In contrast to other provinces like Saskatchewan, New Brunswick, and Nova Scotia, which still rely on coal to varying magnitudes, all coal-fired generators in Ontario were eliminated from the electricity grid by April 2014 (DES). Currently, coal-fired plants generate 40%[5], 20%[6], 62%[7], and 31.61%[8] of electricity in Saskatchewan, New Brunswick, Nova Scotia and Alberta, respectively. However, Canada is planning to phase-out the coal-fired generators by 2030 nationally[9]. Currently, reduced electricity supply from the elimination of coal has been met from increased reliance of nuclear energy as well as higher supply from cleaner and renewable sources. For example, when compared to 2008, the production of electricity by wind generations has significantly increased from 0.9% in 2008 [10] to 6% in 2017[11].

The objective of this research is to estimate econometrically the effects of different sources of energy on wholesale electricity rates. Focusing on wholesale rates is appropriate given the existence of a real time market where purchasers and generators can submit bids and offers for specific quantities of electricity at varying rates. This exercise would shed light on how the considerable shifts in electricity fuel mix since 2009 have impacted wholesale electricity prices. To the best of our knowledge, previous studies of the Ontario electricity market have not focused on the differential impacts of energy sources on wholesale prices. However, wholesale prices are not the only significant determinant of electricity bills. An increasing share of consumer electricity bills has been due to the rise of Global Adjustment (GA) payments. Specifically, Sen [2015] estimates that from 2006 to 2013

[5] http://www.saskpower.com/wp-content/uploads/power_sources_June2017.jpg

[6] Please refer to page 37 on: https://www.nbpower.com/media/759035/2016-2017-annualreport-en_web_ready.pdf?1

[7] https://www.nspower.ca/en/home/about-us/todayspower.aspx#

[8] https://www.aeso.ca/aeso/electricity-in-alberta/

[9] Federal Environment Minister Catherine McKenna during a news conference after a Canadian Council of Ministers of the Environment meeting in Vancouver on Nov. 3, 2017 noted that Canada is going to continue to eliminate coal-fired electricity. For further information on this interview please visit:
1) https://www.thestar.com/news/canada/2017/11/14/canadas-coal-phase-out-alliance-unfazed-by-opposing-us-position-federal-environment-minister-says.html
2) https://www.thestar.com/news/canada/2017/11/12/canada-uk-team-up-at-climate-conference-in-push-to-eliminate-coal-power.html

[10] The summary of electricity produced by different types of fuel in 2008 is available at, http://www.ieso.ca/en/corporate-ieso/media/year-end-data/2008

[11] The summary of electricity produced by different types of fuel in 2016 is available at, http://www.ieso.ca/en/corporate-ieso/media/year-end-data

GA charges have increased from 10% to around 67%. The GA is the difference between the wholesale electricity rate which generators receive as revenue and the guaranteed rate through long term contracts given by the province. There is a common belief that higher GA payments have been due to Feed in Tariff contracts to renewable based generators[12]. However, it is also important to note that some nuclear, coal, gas, and hydro generators have been granted guaranteed rates contracts as well (Wyman [2014]). The question then, is whether the guaranteed rates to these traditional fuel sources, have had comparable effects on provincial GA obligations, relative to the impacts of renewable source of energy.

This paper contributes to the literature by exploiting time-series variation in hourly wholesale electricity prices from January 2009 to August 2014, and estimating econometrically the effects of shifts in hourly specific fuel mix on such prices. To the best of our knowledge, no other study has estimated the effects of changes to fuel mix on wholesale electricity prices. We also estimate the impacts of change in fuel mix on GA payments. The effects of fuel mix supply are identified by the elimination of coal-fired plants, that were responsible for almost 13.75%[13] of total electricity supply in January 2009, and which fell to zero by the end of April 2014. This policy shift arguably provides exogenous identifying variation, as wholesale electricity rates were not considered a primary driver of the GEA. We also attempt to control for the potentially confounding impacts of other factors that could plausibly affect electricity demand and supply such as temperature, relative humidity, and general economic activity as captured through unemployment, and exchange rates.

A conservative estimate of our empirical results is that in recent years a one percentage point reduction in the proportion of coal relative to hydro is associated with a 5% decline in the HOEP. The marginal effects of gas and nuclear based power are similar. On the other hand, a one percentage point increase in wind based power is associated with almost a 10% decline in the HOEP, which is roughly twice the marginal impact of other energy sources. However, over the sample period, wind only constituted a bit more than 3% of total supply.

[12]For more information please refer to: https://news.ontario.ca/mei/en/2017/03/refinancing-the-global-adjustment.html

[13]Based on authors' own calculation.

In other words, while less reliance on coal has resulted in an upward pressure on the HOEP, this has been offset primarily through more nuclear power. Further, we do not find that more wind power has resulted in higher GA payments. Less coal is significantly associated with higher GA payments while more gas power is correlated with a reduction in GA.

The remainder of the paper is structured as follows. The next section discusses the electricity market structure of Ontario[14] and the Ontario Green Energy Act. Relevant studies are discussed in section three. Section four describes the data that have been used for this study and gives a brief summary description of the dataset. Section five details the empirical model. Econometric estimates are detailed in section six. Section seven concludes with a summary of the main results.

2.2 Electricity Market in Ontario

The IESO and Wholesale Electricity Prices

The Independent Electricity System Operator (IESO) is a crown corporation, which runs and oversees the Ontario electricity market. In particular, the IESO operates on a real-time wholesale market in which electricity is supplied as needed. It posts the predicted demand every day for the following month, which allows suppliers to anticipate how much electricity will be needed. As the IESO notes, this forecast includes roughly 1,400 megawatts (MW) more than what has been predicted to account for any unanticipated event that might affect the power system[15]. Generators/suppliers then send their offers to the IESO on how much they are willing to produce and at what price. On the other hand, large electricity consumers, such as industrials, submit their bids on how much electricity they are willing to consume and at what price. The IESO collects both, offers from suppliers and bids from large consumers, until two hours before the electricity is needed.

[14]This section gives a cursory overview of the electricity market in Ontario. For a much more in-depth explanation, readers can refer to Sen [2015], Dewees [2010], Wyman [2014] and Trebilcock and Hrab [2005].
[15]For further information please refer to: http://www.ieso.ca/en/learn/electricity-pricing/how-the-wholesale-electricity-price-is-determined

Afterwards, the IESO starts to accept the offers from the lowest to the highest, until demand is met. In the end, all suppliers are paid the same rate and the wholesale price is set every hour. The Hourly Ontario Energy Price (HOEP) is the average of twelve wholesale market clearing prices in each hour. This means that there is a market clearing price every five minutes [16].

Retail Electricity Prices

In Ontario, consumers are divided into two groups based on their consumption: (1) Small consumers: Residential and small businesses with consumption lower than 250 Megawatt hours (MWh) per year. (2) Large consumers: Any business that uses more than 250 Megawatt hours (MWh) per year. Small consumers are billed for their electricity usage by a Local Distribution Company (LDC) while large consumers are usually billed by the IESO unless they choose to sign a retail contract. Small consumers are either billed based on time-of-use (T.O.U) or tiered rates. Most small consumers pay the T.O.U rates. Both groups can sign retail contracts. Large consumers also fall into one of the following three categories:(1) If the consumer has an interval meter, it pays HOEP. (2) If the consumer does not have an interval meter, it pays a weighted HOEP based on the consumption pattern of its LDC. (3) All consumers have the option to enter fixed-price retail contracts offered by a retailer.

In addition to the IESO, the Ontario Energy Board (OEB) plays a significant role in wholesale electricity market. Among other things, the OEB oversees, set rules and decide the rates that utilities can charge. The OEB ensures a reliable and sustainable energy system[17].

[16] For further details on how the wholesale electricity price is determined in Ontario, please visit: http://www.ieso.ca/Pages/Ontario's-Power-System/Electricity-Pricing-in-Ontario/How-Wholesale-Electricity-Price-is-Determined.aspx

[17] For more details on the role of OEB please visit: https://www.oeb.ca/about-us/what-we-do

Global Adjustment

In addition to the different rates that are explained above, electricity consumers in Ontario pay for the Global Adjustment (GA)[18] on their electricity bills. When it comes to paying for GA, consumers are divided into two classes. Class A consumers are those with average hourly consumption of 5 megawatts (MW) or more. There has been a recent change whereby customers with electricity demand of over 1 MW and up to and including 5 MW can also move to Class A classification[19]. The GA rate for each customer in this class depends on the contribution of that customer to the five peak hours of the year. Every day the IESO publishes information to help Class A consumers predict whether the forecasted peak demand for the next 24 hours could be a top 10 Ontario demand peak during the current year[20]. Therefore, Class A consumers can adjust their electricity consumption and reduce their GA cost[21]

Class B customers are customers with peak electricity demand over 50 kilowatts (KW) and under 5 MW. Class B customers pay for the GA in one of the following forms: (1) The GA is incorporated in the time-of-use (T.O.U) or tiered rate. In this case, customers do not see a separate line in their bills for GA rate; (2) Customers who have retail contracts see a separate line for GA in their bills. The GA, in this case, depends on the billing cycle and can be one of the following forms[22]: (i) First estimate: Published on the last business day of the previous month. (ii) Second Estimate: Published on the last business day of each month. (iii) Actual: Published on the tenth business day of each month for the preceding month. As the names show, the first and second rates are estimates which are calculated based on the last month GA and demand, and the actual rate is based on

[18] Further details on the main components to calculate the monthly GA rate are available at, http://www.ieso.ca/Pages/Ontario%27s-Power-System/Electricity-Pricing-in-Ontario/Global-Adjustment.aspx

[19] For further details about Class A please visit: http://www.ieso.ca/Pages/Participate/Settlements/Changes%20to%20Class%20A%20Eligibility.aspx

[20] Further details on information provided by IESO to track the peak demand hours are available at, http://www.ieso.ca/en/sector-participants/settlements/global-adjustment-for-class-a

[21] For more information on the impact of High-5 program on Class A and Class B consumers, readers can refer to Sen [2015]

[22] For further details on Class B please visit: http://www.ieso.ca/Pages/Participate/Settlements/Global-Adjustment-for-Class-B.aspx

the actual demand and the GA rate. These different mechanisms do not affect the total GA that has to be paid. Therefore, irrespective of how different classes of consumers are sharing the payment for the total GA, this total is unaffected.

Payments to Generators in Ontario

Each generator in the Ontario electricity market is paid in one of the following ways: (1) Generators whose offers are accepted and dispatch electricity- are paid at the market clearing price. These are generators without guaranteed rates under long term contracts; (2) Renewable, natural gas and nuclear generators that have contracts with Ontario Power Authority (OPA)[23]- are paid either based on the Feed-In-Tariff (FIT) contracts under the Green Energy Act[24] or long-term power-purchase agreements (PPAs) (Wyman [2014]). (3) Large hydroelectric and nuclear generators that are operating based on a regulated rate- paid at their guaranteed operating price. This rate is set by the OEB (Wyman [2014])[25]. Both the OEB and the OPA contract rates have been higher than the market clearing price (HOEP) since 2005 and therefore the difference is covered by the GA (Sen [2015]). In particular, part of the GA is allocated to cover the difference between the regulated price and the market clearing price (Wyman [2014], Sen [2015]).

The Ontario Green Energy Act

In 2009, Ontario introduced the Green Energy Act (GEA), which promotes the expansion of renewable energy technology and conservation plans. One of the objectives of the GEA was to decrease Ontario's dependence on fossil fuels and improve the air quality. Therefore,

[23]OPA was established in 2004 by the government of Ontario and in January 2015 merged with the IESO.

[24]The FIT program is explained in the next subsection.

[25]In addition to the mentioned categories, suppliers whose offers have not been accepted are paid an "Operating Reserve" that is determined by the IESO. This payment is made to generators for their availability to produce energy when demand spikes or a generator unexpectedly is not able to produce for any reason. For further information on the operating reserve markets please refer to: http://www.ieso.ca/sector-participants/market-operations/markets-and-related-programs/operating-reserve-markets

the Feed-in-Tariff (FIT) program was introduced. The primary focus of the FIT program is in renewable energy investments. In particular, the program is open to any renewable energy developer with a project to produce renewable energy more than 10 kilowatts to 500 kilowatts. The market participants in this program can sign a contract to sell the generated renewable energy to the province at a guaranteed price[26].

One of the main achievements of the FIT program is the phase out of coal-fired generators in 2014. The success of the FIT program includes not only the termination of coal-fired generators but also the expansion of renewable energy production in Ontario. Since 2014, solar, biofuel and wind power generations substitute the electricity that was produced by coal generations. Notably, the production of electricity by wind power generation increased significantly. In 2008[27], 14.5% and only 0.9% of electricity were produced by coal and wind power generators respectively. However, in 2017 the production of electricity by wind power generations was increased to 6% while coal-fired generations were fully phased out[28].

2.3 Literature Review

Several recent studies such as Sen [2015], Wyman [2014] and Dewees [2010] have identified that the increased pressure on the generation system and excessive electricity consumption are primary determinants of the way in which an electricity system is structured. In trying to design an electricity price paradigm that not only encourages conservation but also reduces strain on the generation system, the government of Ontario has taken many approaches during the last decade, some of which have made the province of Ontario less

[26] For more information on the FIT program please refer to: http://www.energy.gov.on.ca/en/fit-and-microfit-program/ and http://www.ieso.ca/sector-participants/feed-in-tariff-program/overview

[27] The summary of electricity produced by different types of fuel in 2008 is available at, http://www.ieso.ca/en/corporate-ieso/media/year-end-data/2008

[28] For the most recent information on share of each fuel type in Ontario's electricity market please visit: http://www.ieso.ca/Pages/Power-Data/supply.aspx

attractive for new electricity consumers[29] (Sen [2015], Dewees [2010], ONT). In addition, detailed examination of Ontario's electricity market by researchers such as Sen [2015], Dewees [2010] and Wyman [2014] shows that current Ontario's electricity consumers are also keen to see a change in the electricity market: They want to be able to enjoy lower electricity prices with less price volatility in the electricity wholesale market. For example as Wyman (2014) states "Ontario electricity consumers stand to benefit from lower electricity prices and less risk if the province moves to a capacity market for obtaining generation." (Wyman [2014]).

To better serve electricity consumers, the province of Ontario has engaged in redefining electricity prices by looking at the electricity markets from different angles. Ontario has not only focused on wholesale market prices (supply side) but also taken initiatives to redefine prices that retail and small business consumers pay (demand side). Despite their stated objectives, each policy has made little progress so far. This is mainly because of various problems that have arisen while implementing these policies. In what follows we discuss some of the government's most popular programs and the problems within each of them, as recognized in the literature to date. In addition, this literature review focuses on recent empirical based studies of Ontario electricity demand and the supply side of the market. As noted by Choi, Wai Hong [2013], there are, of course, earlier time-of-use (TOU) econometric studies of residential, commercial, and industrial demand in Ontario during the 1980s and 1990s, such as Yatchew [2000], Mountain [1994], Mountain and Lawson [1992], Mountain and Lawson [1995], and Ham et al. [1997]. More recent studies are Choi et al. [2011] and Genc [2016]; however, the focus of these studies is on real time wholesale electricity prices on demand by industrial customers.

2.3.1 Small electricity consumers (Demand side)

At the small consumers level (such as a household), the government has focused on upgrading the infrastructure by installing smart meters. The intention behind installing the

[29] Some of these approaches are the introduction of time-of-use (TOU) in 2006 and the High-5 program in 2011.

smart meters was not only to conserve energy and manage demand (ELE) but also decrease the need for new generation investments (ONT). Smart meters have been utilized to measure electricity consumption at each time of day. Once the smart meters were installed, it was then necessary to adopt a time-of-use (TOU) signal pricing mechanism. Such transitions were believed to help signal electricity users to manage their bills by modifying their electricity consumption patterns (ELE). Nevertheless, the strategy of having smart meters and the transition to TOU pricing have not escaped criticism. The most important of these criticisms is that smart metering failed to note that high-income consumers are not responding to price changes. The bill increases were very negligible (ELE) and could not curb the demand as expected (ONT). It has been suggested, however, that were TOU pricing twice or three times higher at the peak demand period, it would decrease demand by 3 to 6 percent (Faruqui and Sergici [2010]). The rationale is that consumers would recognize major savings in their bills by shifting their consumption to off-peak periods. In addition, researchers challenge the widely held view that although smart meters and TOU would benefit some consumers, it cannot be considered fair to some small businesses that cannot cut their electricity use in peak demand periods. For example, restaurants have to operate even during the peak hours (Dewees [2010]). Moreover, it is noteworthy that 20 percent of Ontario's residents who live in multi-residential apartments are completely isolated from TOU price signals (Dewees and Tombe [2011]). This occurs because 70 to 90 percent of these buildings are bulk metered versus individual suite-metering (Dewees and Tombe [2011]). Research shows that moving from bulk-metering to individual suit-metering would be economically beneficial only if the cost of installing the meters is ignored.

Tables B.1 and B.2 in the Appendix present various studies that investigate the impacts of metering and sub-metering on consumer electricity demand respectively. These studies have explored a number of different factors that influence electricity consumption patterns when meters are installed. For example, Gilbert and Zivin [2014] discuss how information signals such as receiving electricity bills would decrease consumption in the following week more than in other weeks of the month (Gilbert and Zivin [2014]). On the other hand, Martin and Rivers [2015] show that the in-home electricity display (IHD) and TOU pricing can couple and decrease a household electricity consumption by 3% in Ontario[30]. They found that the decrease in household electricity consumption were more visible in hours of the day with more extreme temperature (Martin and Rivers [2015]). Other factors, such as weather conditions (Sen [2015], Munley et al. [1990], and Kavousian et al. [2013]), adoption of energy efficient appliances (Kavousian et al. [2013] and McCoy and Lyons [2014]) and fixed-effects of time trends (Jack et al. [2015] and Sen [2015]) have been recognized by scholars to influence electricity consumption. The results drawn from the literature are consistent and show a decreasing trend in electricity consumption when meters are installed; however, most studies in the field of household electricity consumption have only focused on short term data in addition to considering specific groups of consumers.

On the other hand, in spite of the crucial role of the supply side of the electricity market, much less is known about the factors at play in this side. Analyzing the system in which the supply side of the electricity market works would not only provide direction for aggregate demand management to decision makers but also result in addressing the research gap in this area. Therefore, the following subsection provides an overview of the supply side of Ontario's electricity market as discussed in the literature.

2.3.2 Supply

On the supply side of the electricity market, most research has focused on policies that have either encouraged expansion of existing capacity or the possible extension of markets to generation capacity. In this regard, the government of Ontario took the initiative to secure the supply of electricity by creating the Ontario Power Authority (OPA) in 2004. Using central contracting, the OPA has procured new generation and signed twenty-year power purchase agreements (PPAs) with nuclear plants, which locked down prices for long time periods (Wyman [2014]). This allowed nuclear plants to focus on refurbishments and renovations. Although PPAs will be in effect for almost another half decade, experiencing the rising power costs encouraged the IESO to look for other initiatives to tackle the

[30]The dataset for this study contains hourly data on electricity consumption of around 7000 households in Ontario from 2012 to 2014 who are given IHD.

problem. A recent study by Wyman (2014) traces the initiatives that the IESO took in this regard. For example, the IESO has embarked on introducing a capacity market for Ontario (Wyman [2014]). In 2014, the IESO started to invite interested stakeholders to discuss designing an effective capacity auction (the so-called capacity market) and published the Capacity Auction Stakeholder Engagement Plan in October 2014 (IES).

In the capacity market, as Wyman states "... generators receive payments for agreeing to be available to run at some period in the future" (Wyman [2014]). Therefore, a capacity market ensures the adequacy of supply and balances prices (Dachis and Carr [2011]). By drawing on the concept of the capacity market, Wyman has been able to argue that moving away from PPAs and relying on the capacity market brings not only more transparency in setting prices, but also a more efficient and trustworthy electricity generation system (Wyman [2014]). Furthermore, the IESO believes that construction of a capacity auction would ensure "... future resource needs of Ontario's electricity system and provide the flexibility for new and existing technologies to compete on an even footing in the marketplace." (IES). This is definitely efficient, as ensuring an appropriate pricing system for new coming generators in Ontario should be a priority for decision makers. Currently, each generator is contracted separately to receive a fixed price. If the HOEP is not sufficient to pay the guaranteed price to generators, consumers will pay the difference through the Global Adjustment (GA). If the HOEP is more than what has been guaranteed to pay to generators, consumers would receive money and so the GA would be negative. In addition, the GA includes the cost of conservation and demand management programs.

It is worth noting that GA has stayed positive since 2007 and it was negative only once in March 2014 (-0.27). This would imply that the wholesale prices (HOEP) were not sufficient to cover generators guaranteed prices; therefore, consumers have been paying the difference between HOEP and contracted prices of generators. Detailed examination of GA and HOEP from 2005 to 2014 by Sen (2015) revealed an increasing trend in total GA, and unsurprisingly, a decreasing trend in total HOEP prices from 2006. In regard to the increasing GA and in another attempt to reduce electricity consumption by major consumers in Ontario, the High-5 GA program was introduced in 2011. The High-5 GA program is aimed to reduce the electricity consumption of large industries during the 5 hours of peak demand each year. Two classes of consumers have been identified within this program: Class A: Consumers with an average hourly peak demand of 5 MW or higher who are charged based on their energy used during peak hours[31]. Class B: Consumers with a peak demand of 5 KW to 5 MW who pay the actual GA rate. The program gives enough incentives to Class A consumers to reduce their electricity consumption; however, not all industries are able to reduce their consumption since they are unable to make any adjustment in their production schedule (Sen [2015]). In addition, this program has transferred the GA from one class of customers (Class A) to another (Class B) (Sen [2015]).

In summary, empirical work on the supply side of the market has been limited. Therefore, there is an urgent need to address the link between wholesale market prices and electricity supply, and study the magnitude of the effect of each generator on electricity prices in Ontario during the past years. To the best of our knowledge, although some research has been carried out on the GA pricing system and electricity conservation by households and industrial consumers, the effects of fuel mix on the HOEP and GA have not been examined within an econometric framework. In fact, we have been unable to locate any other econometric study, which has examined the effects of generation fuel mix on some measure of wholesale or retail electricity prices.

The purpose of this study is to explore the relationship between prices (HOEP and GA) and the hourly supply of each generation during 2009 to 2014. Given the lack of corresponding research, we believe that this exercise is worthwhile in order to understand the relationship between fuel mix and HOEP and GA payments should help decision makers to set the right prices for new generator contracts (within the newly introduced capacity market) which, in turn, will lessen the burden of GA on all electricity consumers in Ontario. Further, the results of this paper may be used to direct the government of Ontarios investment on the efficient combination of generations in the electricity market.

[31] There has been a recent change whereby customers with electricity demand of over 1 MW and up to and including 5 MW can also move to Class A classification. For further details about Class A please visit: http://www.ieso.ca/Pages/Participate/Settlements/Changes%20to%20Class%20A%20Eligibility.aspx

2.4 Data Description

The dataset for this study contains HOEP and GA prices in addition to the generations' hourly production from 2009 to 2014. Both the prices and generations' hourly production data are obtained from IESO. Also, we incorporate the data for hourly average temperature and relative humidity along with monthly exchange rate and the unemployment rate in Ontario. The data for temperature, relative humidity, Exchange and the Unemployment rates are gathered from Statistics Canada. Brief summary statistics are shown in Tables 2.1 and 2.2.

Table 2.1 shows general summary statistics for the dataset. As reported in this table, most of the electricity production comes from nuclear generators. Hydro and gas energy rank second and third in power generation. Some interesting observations are the reported negative electricity market prices and zero productions of generations. Table 2.2 indicates the number of incidents in which value of the variables reported is zero in the dataset. There are 1338 events in the dataset where the HOEP is negative. The negative HOEP stem from periods of low demand coupled with continuous production of generations. Some generators such as nuclear and wind cannot adjust production immediately because of their nature. Therefore, the HOEP significantly decreases and even becomes negative during these periods.

When market price (HOEP) is insufficient to meet the guaranteed rates paid to generators, GA is collected from the consumers to pay the difference between the market price and the regulated and contracted generators' rate. In this regard, GA and HOEP add up to meet the generators' regulated price. Therefore, the HOEP price can be negative while generators receive the guaranteed payment. Figures 2.1 and 2.2 show the monthly average HOEP and the GA prices since 2009 to 2016. As can be seen from these two graphs, since 2009 the HOEP is decreasing and the GA shows an increasing trend in general[32].

Regarding the zero electricity production incidents, coal-fired generations hold the

[32] The sharp increase in the HOEP and the sharp decrease in the GA in 2014 are due to data availability. We do not have the HOEP prices for the last four months of 2014. Therefore, for comparison purposes, we dropped the GA data for the last four months of 2014 in Figure 2.1.

record among all other generations. This is because Ontario was trying to phase out the burning of coal to produce electricity in all of its five coal power plants. Thunder Bay Generating Station was the last coal-fired plant, which ceased power production in April 2014 and made Ontario a coal-free province. Figure 2.3 shows the average monthly coal-fired generations since 2009, in which the sharp decrease in the production of electricity by coal-fired generations is visible.

Table 2.3 shows the summary description for the HOEP from January 2009 to August 2014 averaged over months. As shown in Table 2.3, there is a marked decrease in the average HOEP from 34.68$ in March to 25.81$ in April, and it levelled off since then for Spring months. The most likely causes of the decline in HOEP are Spring run off and heavy rains that disperse extra water into hydraulic generators. This can increase the supply of electricity and result in the decrease of HOEP. Also, during the Spring and Fall months the need to run air conditioning and heaters is very low; as a result, electricity consumption drops. The low demand in these seasons can give rise to more depressed HOEP [33]. As Winter hits the mean HOEP increases sharply from 29.79 in December to 39.75 in January. This can be explained by lower supply from hydraulic generators and excessive consumption of electricity by heaters.

2.5 Empirical Model and Results

2.5.1 Model Framework

The aim of this study is to explore the effects of the hourly electricity supply by each generation on the Hourly Ontario Energy Price (HOEP) and Global Adjustment (GA) during January 2009 to August 2014. Two approaches were adopted to evaluate both the magnitude of such effects and the responsiveness of prices to the supply of each generation.

In the first approach, we structured the data in a Panel format and ran Generalized Least Square estimation. The random effect of hours is captured in this method. In the

[33] For more information please refer to: https://www.greenhousecanada.com/energy-edge/procurement/electricity-rate-price-shock-in-ontario-this-month

second approach, we focus on the Time-Series nature of the dataset. We ran the Unit Root Test to find out if the time-series dataset is trend-stationary. Since we rejected the null hypothesis that the series contains a unit root, we concluded that the time-series are trend-stationary[34]. Therefore, we used the same set of variables as in the first model to be able to compare the ability of the two methods in explaining the proposed relationship between prices and supply. In both regression methods, we use dummy variables to account for the fixed effects of years, months and days of the week on power generations.

Thus, the price function estimated by the first model in this paper reads as follow:

$$LnP_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 H_{it} + \beta_3 G_{it} + \beta_4 N_{it} + \beta_5 O_{it} + \beta_6 W_{it} + \beta_7 Total_{it} + \beta_8 Temp_{it} + \beta_9 Rel.Hum_{it} + ExchangeRate + UnemploymentRate + Y + M + DW + H + \varepsilon_{it}$$

In the Panel dataset:

i = The Panel ID or Panel Variable which are the 24 hours of a day (i.e., 1,...,24);

t = The panel's Time Variable for duration from 1st of January 2009 to 31st of Aug 2014 (i.e., date);

LnP_{it} is the natural logarithm of the Hourly Ontario Energy Price (HOEP) in hour i at time t;

C_{it}, H_{it}, G_{it}, N_{it}, O_{it} and W_{it} are the percentage of electricity generated by coal-fired, hydro, gas, nuclear, other type of generations and wind in hour i at time t respectively. The generations' productions are the key variables of interest;

$Total_{it}$ is the total electricity produced in hour i at time t;

$Temp_{it}$ and $Rel.Hum_{it}$ are the Ontario average temperature and relative humidity in hour i at time t;

$ExchangeRate$ is the Canadian monthly cents per United States dollar spot rate. $UnemploymentRate$ is the estimated percentage of the unemployment rate in Ontario that is seasonally adjusted;

Y is a vector of year fixed effects. M captures month fixed effects and DW and H are dummy variables for days of the week and hours;

[34]The result of the Dickey-Fuller for unit root test is presented in the Appendix (Table B.3)

ε_t is an idiosyncratic error term.

The focus of this study is on estimating β_1 to β_6 which yields the percentage change in hourly electricity price in Ontario in response to a one percentage point increase in the average electricity production by each type of generations. Lower cost sources of electricity are dispatched first, thereby having a larger effect on HOEP. In this regard, we expect a larger coefficient estimates for wind power generation which has very low to zero marginal cost of production; and a higher coefficient for coal, gas and nuclear power generations which have higher marginal cost of production than wind.

The reason to consider the total electricity supplied is to capture the effect of demand on the HOEP. Since the market price (i.e., HOEP) is determined when the market is at equilibrium, therefore, the amount of total electricity supplied is not far from the total electricity demanded. In this regard, in all regressions, we considered the total electricity produced in addition to the proportional values of electricity generated by each generation to capture the effects of demand on the HOEP. In addition, since in this study differences in cost of production are captured by considering fuel mix in each hour, we needed to use the proportional values rather than absolute values of electricity produced by each generation.

In the Time-Series model, we test the effect of the electricity generations' production on hourly price through the following reduced form specification:

$$LnP_t = \beta_0+\beta_1 C_t+\beta_2 H_t+\beta_3 G_t+\beta_4 N_t+\beta_5 O_t+\beta_6 W_t+\beta_7 Total_t+\beta_8 LnP_{t-24}+\beta_9 LnP_{t-25}+ \beta_{10} Temp_t+\beta_{11} Rel.Hum_t+ExchangeRate+UnemploymentRate+Y+M+DW+H+\varepsilon_t$$

Like before, we are interested in checking the magnitude and sign of β_1 to β_6; however, in the next section we are going to explain briefly how the introduction of other variables in the model affects the magnitude and sign of the key variables of interest. We are also interested in comparing the effect of each generation's production in terms of the sign and magnitude on the GA. Therefore we ran the following GLS model:

$$LnGA_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 H_{it} + \beta_3 G_{it} + \beta_4 N_{it} + \beta_5 O_{it} + \beta_6 W_{it} + \beta_7 Total_{it} + \beta_8 Temp_{it} + \beta_9 Rel.Hum_{it} + ExchangeRate + UnemploymentRate + Y + S + M\varepsilon_{it}$$

In the Panel dataset:

$i =$ The Panel ID or Panel Variable which are the 12 months of a year;

$t =$ The panel's Time Variable for duration from 2009 to 2014 (i.e, years);

$LnGA_{it}$ is the natural logarithm of the Global Adjustment in month i of year t;

Y is a vector of year fixed effects. M captures month fixed effects and S is a dummy variable for seasons;

All generation's production and weather variables are averaged at the monthly level.

In addition to the GLS regressions, we also focused on Time-Series nature of the GA monthly data and ran the following Time-Series regressions on GA:

$LnGA_t = \beta_0 + \beta_1 C_t + \beta_2 H_t + \beta_3 G_t + \beta_4 N_t + \beta_5 O_t + \beta_6 W_t + \beta_7 Total_t + \beta_8 LnGA_{t-1} + \beta_9 Temp_t + \beta_{10} Rel.Hum_t + ExchangeRate + UnemploymentRate + Y + S + M\varepsilon_t$

Where:

t is the monthly date variable (i.e., January 2009 to August 2014).

Using a fixed-effect model, it was possible to control for characteristics within categories of the year, month and day of the week that might affect the left-hand side variable (HOEP or GA). The evidence of year fixed-effects can be clearly seen in the case of high precipitation or heavy winds in one year; this can result in increased electricity production from hydro power or wind generations and decrease HOEP prices. Month fixed-effects are best exemplified during fall and spring months when hardly any heaters or air conditioning are running. Also, low demand during weekends can rationalize the need for considering the day of week fixed-effects in this model.

Hourly temperature and relative humidity are considered to control for the effect of weather condition on the production of electricity by generations such as wind and hydro. Hourly average Ontario temperature and relative humidity are constructed from hourly temperature and relative humidity of five major cities in different geographical regions in Ontario: Toronto, London, Ottawa, Hamilton and Thunder Bay.

Besides, consideration of Exchange rate and Unemployment rate enables the model to control for economic conditions in Ontario that might impact the business, change the electricity supply and eventually affect prices.

In the Time-Series model we use the lagged values of the response variable (Price) to incorporate feedback over time. Specifically, we see that observations at time t are likely to be correlated with observations at time $t-24$ and $t-25$ based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). In the next section, we explain why and what other lag structures have been considered in the model, and we discuss the results.

The production of electricity by each generation is in percentage format; therefore, when running regressions we omit hydro from both equations to avoid collinearity between independent variables. In the same way, we do not consider month dummies with Exchange rate and the Unemployment rate in the same regression. This is because both the Exchange rate and Unemployment rate in our dataset are reported monthly. Incorporating these variables with month dummies in the same regression may lead to over-specification in month effects.

Before controlling for time-invariant variables that might affect the model (i.e., using time-specific fixed-effects), it was important to run the basic regression model within each defined model without considering any dummy variables on the pooled data for comparison purposes. The following section discusses the results of both the baseline estimate of price function and breakdown of the model with different specifications in each model model.

The major limitation of these analysis is the possible presence of endogeneity which could have been resolved by using Instrumental Variables (IV) for the production of electricity by each type of generation (such as fuel prices or marginal cost of production by each generation). However, choosing a desired set of IVs is hard in this analysis. This is mainly due to data limitation as we are interested to preserve the hourly dynamics in our analysis and the fuel prices or marginal cost of producing electricity by each generation are not available at the hourly level. Therefore, we acknowledge the fact that the calculated coefficients might be biased.

2.6 Results

In this section, we discuss the outcome of the analysis when different methods of estimation are used. The first column in all tables (except table 2.10) shows the summary statistics of the main explanatory variables (production by different sources of energy) to reflect the scale of production by each energy source in the considered time periods. Table 2.4 compares the results obtained from the panel data analysis of hourly energy prices on the pooled data from 2009 to August 2014. We then employ the time-series model where the lagged prices are considered. While Tables 2.4 and 2.5 use the whole available dataset, the remaining tables use different samples. This is to compare the ability of the proposed model in explaining the variability in HOEP during $2010 - 2011$ and more recent period of $2012 - 2013$. When dividing the data into two sections, we ignored the data for 2014 since we do not have the data for the full year. Further, in order to have two equal time intervals, we ignored the earlier data for 2009.

In Table 2.4 results of estimating different types of fuel mix on natural logarithm of HOEP in isolation from any dummy and temperature variables and economic factors is shown in the second column (Reg(1)). Column 3 includes variables that reflect the weather conditions in addition to the Exchange and the Unemployment rate (Reg(2)); in column 4, fixed effects for years, months, days of the week and hours have been controlled for (Reg(3)). To conserve space, coefficients of different dummies that have been considered in this study are not reported. We have also accounted for fixed effects of days of the month; however, the results were not significant and therefore are not reported in this research. Column 5 in this table considers all listed independent variables except month dummies and total electricity production (Reg(4)). The last column in this table represents the result of the fully specified model (Reg(5)). All coefficients and their robust standard errors are reported in the tables.

As can be seen in Table 2.4, in all specifications the coefficients of wind and nuclear are negative and statistically significant at 0.1%. The coefficient estimate suggests that relative to hydro, a one percentage point increase in electricity produced by wind and nuclear generation results on average in 5.6%-10% and 3%-5% decrease in HOEP prices respectively. On the other hand, whenever significant, the coefficient of gas shows an opposite trend; a one percentage point increase in electricity production by Gas generations on average increases HOEP by around $1\% - 2\%$. This result is comparable to that shown by the coefficient of coal. An increase in production of electricity by coal generations has positive effect on prices and it suggests that on average a one percentage point increase in coal generation's production results in a $2\% - 3.7\%$ rise in HOEP. The ability to explain the model using GLS estimation is increased in the last columns when time dummies and all other explanatory variables are considered. In all of these cases the reported R^2, which shows the ability of the proposed model in explaining the variation in HOEP, is around $21\% - 29\%$.

Turning now to the Time-Series estimation of hourly prices, the five Tables of 2.5 to 2.9 contain different time periods and price lag selections. Table 2.5 consists of Time-Series estimation of the HOEP when different model specifications similar to ones in Table 2.4 are considered. In this analysis, we were interested to find out if the consideration of lagged prices as explanatory variables can be added to the model. The two most common, Akaike Information Criterion (AIC) and Bayesian Information, Criterion (BIC), are used to determine what lags to use. AIC and BIC are two statistics that report the lag selection when the data is defined as the Time-Series dataset. Both AIC and BIC suggest that the optimal numbers of price lags are 24 and 25. In this regard, both lags are added to the model, and the results are presented in Table 2.5.

The first regression analyses in Table 2.5 examined the impact of different types of fuel mix on the HOEP in the absence of the other explanatory variables. Then moving to regression (2), weather, Unemployment and Exchange rate variables are added to the model. Regression (3) considers the estimation of the model when controls for time trends are captured by time dummies. In regression (4), we considered the model when all explanatory variables except total electricity production and month dummies are considered and, as before, the last regression is the estimation of the fully specified model. Based on the results from the Time-Series model, the coefficients of wind and nuclear are negative and highly significant at 0.1% level. The results suggest that a one percentage point increase in production of electricity by wind (nuclear) relative to hydro will decrease HOEP by roughly $6.2\% - 9.4\%$ ($3\% - 4.3\%$). This is similar to what the GLS model reported earlier. In addition, production of electricity by wind generations has the most pronounced effect on HOEP, although it only takes on average 2.7% of the electricity market share.

As shown in Table 2.5, consideration of lagged electricity prices is important in this model, and the coefficients are significant at 0.1% level. Besides, the proposed model can explain around 37% of the variation in HOEP, which is higher than what the GLS model proposed earlier. On the other hand, while the coefficient of coal has a positive sign in all model specifications like before, the coefficient of gas does not show a consistent pattern. In the basic regression, the coefficient is reported with a positive sign and highly significant, whereas it is shown to have a negative impact on HOEP and is still statistically significant in regressions 3 and 5. Besides, the coefficient of gas is reported to have a lower effect on HOEP in general when compared to the coefficients reported by the GLS model, likewise, the coefficient of Coal. In general, the reported adjusted R^2 in the Time-Series model is higher than in the GLS model. When the GLS model is shown to have the R^2 around 28%, the Time-Series model reports an adjusted R^2 of around 37%. In this regard, we are going to rely on the Time-Series models in the remaining part of hourly regression results.

Having discussed the two models of Time-Series and GLS, the next section of the results addresses a brief comparison between two periods: a period from 2010 to 2011 and a more recent period of 2012 to 2013 are constructed from the dataset. The purpose of this division is not only to evaluate the significance and magnitude of different types of generations' production of electricity on explaining the variation in the HOEP but also to compare the magnitude of coefficients within these time periods. On the other hand, although AIC and BIC suggest the consideration of the 24th and 25th lags for the HOEP, we are more interested in short-term effects of previous prices. In this regard, we consider the 2nd to the 9th price lags plus the average prices of yesterday and the day before as explanatory variables in the following regressions. As before, we ran five regressions with different model specifications in each period; also, we ran the fully specified model in which the HOEP has its original value and is not transformed to natural logarithmic version. The results are shown in the last column as regression (6) in Tables 2.6 and 2.7.

The results, as shown in Table 2.6, indicate that among all fuel types, the wind generation has the most profound effect on explaining the variation in the HOEP relative to hydro. A similar result can be found in Table 2.7 where we analyze the most recent data of $2012-2013$. On the other hand, the coefficient of gas is statistically significant only in the third, fifth and sixth regressions where we controlled for time-fixed effects. Its negative sign suggests that on average a one percentage point increase in electricity produced by gas generations will decrease HOEP by around $0.6\%-0.7\%$. The small magnitude of gas generators disappears when we turn our attention to the result in Table 2.7. Despite the reported result for gas in Table 2.6, Table 2.7 shows a negative and statistically significant coefficient for gas in all considered regressions. In addition, the effect of gas on the HOEP is higher, at around $2.8\%-5\%$ for every one percentage point increase in production of electricity by gas generations (relative to hydro).

The most striking result to emerge from the comparison of the two tables is that the effect of production of electricity by wind, nuclear and gas generations on prices has increased in more recent years of $2012-2013$. In contrast, other types of generations have shown lower effects over the past years. Moreover, coal generations have not shown a consistent pattern, and wherever significant, the coefficient of coal is negative and its magnitude changes from $0.05\%-1\%$ and $1\%-4\%$ in Table 2.6 and Table 2.7 respectively.

Regarding the considered lagged prices, the result suggests that the only significant lag in all regressions is the second lag. In addition, although the average prices of the day before are shown to be statistically significant in all periods, the average prices of two days before are only significant in the more recent period of $2012-2013$. The two weather variables of average Ontario temperature and average Ontario relative humidity that are considered in regressions (2) to (6) are worth noting; however, the purpose of recruiting them in the model is to control for any changes in electricity production due to weather conditions that can further affect prices, and they are not variables of interest. In this regard, we are not going to focus on the interpretation of those variables in details; however, in general, the results show that whereas average temperature plays a significant role in explaining price variations in all models, relative humidity is mostly significant in the more recent period. On the other hand, while the coefficient of temperature is always negative, the coefficient of relative humidity is positive. This result suggests that a higher temperature would result in a decrease of HOEP.

In both Tables 2.6 and 2.7, following the addition of more explanatory variables, the adjusted R^2 rises; however, in Table 2.6, it is only slightly higher in the third regression where we only consider to control for the different time trends. Also, the adjusted R^2 is higher in all regressions of Table 2.7 compared to the similar regressions in Table 2.6. With almost successive increases in adjusted R^2 from regression (1) to regression (5), we conclude that the fully specified model is worth considering in further analysis.

We also ran a sensitivity analysis to check the robustness of the results. Table 2.10 shows the results from time-series analysis when the cluster-standard errors (at day level) and Newey-West standard errors in which we assume that the error structure is heteroskedastic autocorrelated up to lag (1)[35] are considered[36]. We specifically focused on the fully specified model in both periods of $2010-2011$ and $2012-2013$. Regression (1) and (3) show the results of the regressions when the standards errors are clustered at day level in each period. Regression (2) and (4) consider the Newey-West standard errors. As the results show, all of the independent variables in the model are statistically significant at the same level as reported in regression (5) in Table 2.6 and 2.7. In $2010-2011$ the only exception is the coefficient of "Other" that is significant at 0.1% level in Table 2.6 whereas it is reported to be statistically significant at 5% level in Table 2.10.

Having discussed the differences between the two periods, in the next step, we scrutinize the effects of production of electricity by each type of generation on the HOEP when the data are divided seasonally in each time interval. In what follows, we run the fully specified model for each season in each period and compare the results that are shown in Tables 2.8 and 2.9. We begin our analyses by looking at the results from Winter $2010-2011$ and Winter $2012-2013$. A comparison of the two results reveals that not only the share of

[35]We considered the lag (2) and lag (3) and the result did not vary significantly.

[36]In addition, we used the weekly Bank of Canada energy price index as an IV for coal. We also added the 4 weeks and 8 weeks lag of the energy price index in the regressions. The coefficients of interest (except "other") in the more recent years of 2012-2013 showed a consistent pattern with what we have found earlier. We did not include these sensitivity analyses in this paper since we believe that we should have instrumented the hourly coal with the relevant variable at the same frequency.

production of electricity by wind generations has doubled in the more recent dates, but also the effect of it on the HOEP. Wind generations in Ontario accounted for 2.19% of electricity production in Winter $2010-2011$, whereas this amount was almost doubled (3.91%) in Winter $2012-2013$. The reason that the production of electricity by wind generation (relative to hydro) decreases the HOEP is the relatively less expensive cost of producing electricity by wind generations. On the other hand, although the electricity produced by nuclear generations decreased by almost 1.5%, surprisingly the negative effect of it on the HOEP increased from 6.7% to 10%. The opposite trend, however, can be seen in the production of electricity by gas generations. Gas generations increased their market share from 12.33% in Winter $2010-2011$ to 15.39% in Winter 2012-2013. This 3% rise in production reflected a tripled negative effect on HOEP prices. The coefficient of gas increased in absolute value from 4.5% to 11%. This result shows that a one percentage point increase in production of electricity by gas (relative to hydro) generations on average decreases HOEP by 11%. Interestingly, whereas coal generations decreased production of electricity to half (from 6.10% in Winter $2010-2011$ to 2.92% in Winter $2012-2013$), the negative effect of this on HOEP increased from 4.8% to 7.7%.

The economic reason for such surprising trends in the effect of coal, gas and nuclear generations on price can be explained as follow. Since Ontario was moving away from coal-fired generations and was investing more in renewable energy sources like wind, solar and biofuel, we see a dramatic decline in the percentage of electricity produced by coal and an increase in wind and other (solar and biofuel) type of generations in recent years. On the other hand, as noted by Gallant and Fox [2011] and Trebilcock [2017] irregularity of production of electricity by wind and solar power generation made Ontario to rely more on gas generation in order to accommodate any unpredictable fluctuations in electricity production by wind and solar power generation. As the less expensive coal became more scarce in the Ontario electricity production process, its effect on price increased. For example, in Winter 2010-2011 the share of coal was 6.10%, which decreased to 2.92% in Winter 2012-2013; on the other hand, its effect on HOEP prices almost doubled. In particular, a one percentage point increase in production of electricity by coal-fired generations decreased HOEP by 4.8% in Winter 2010-2011 and by 7.7% in $2012-2013$. In addition, further increases to renewable and gas slightly decreased the operation of nuclear plants, which in return had a similar effect to coal.

The Spring trend differs from what happened in Winter time. For example the share of wind generations in the production of electricity went up from 2.20% in $2010-2011$ to 3.19% in $2012-1013$; however, the effect of it decreased by 3% (from 10% to 7%). On the other hand, the more surprising result emerges from the other type of generations (solar, biofuel and etc.). Although the share of production of electricity by other type generations increased by only 0.05% in the market, the magnitude of the effect of it on the HOEP sharply increased from 0.02 to 0.13 in absolute value. It seems possible that these results are due to Ontario's transitioning process from using less coal-fired generations and investing more in green energy generations. This is coupled with the weather conditions in Spring that allow more production by solar power generations and essentially have a larger effect on prices.

Comparing Summer of $2010-2011$ with the Summer of $2012-2013$, as the coal generations lose their share in the electricity market, all other types of generations except gas, escalate their production. The magnitude of coefficients of all type of generations including gas increased, which further enhances the ability of the model to explain changes in the HOEP. The adjusted R^2 increased from 43% in Summer $2010-2011$ to 52% in Summer $2012-2013$. A similar trend can be seen when comparing the results of Fall $2010-2011$ with Fall $2012-2013$; however, the adjusted R^2 in Fall $2012-2013$ increased more substantially from 27% to 51%.

What stands out in these comparisons is the effect of wind generations: the production of these increased slightly but showed a relatively higher effect on price. This trend is repeated in all of the results tables. A possible explanation for such a trend is the less expensive cost of electricity production by wind generations. Although the sunk cost of wind generations is high, once the infrastructure is in place the variable costs of producing electricity by wind generations are considered to be low[37]. On the other hand, since the low cost sources of electricity are dispatched before higher cost sources, firms generating

[37]For further details on the cost of wind power generations please refer to "The economics of wind energy: A report by the European Wind Energy Association", page 21, Krohn et al. [2009].

wind power are bidding very low and undercut the supply curve. Therefore, even though the production of electricity by wind power plants have increased slightly over the past few years, the effect of the wind power generation on prices is larger than the effect of other types of power generation.

In the final part of the price analysis, we investigate the effect of electricity production by different types of generation GA. As IESO states, "The global adjustment (GA) is the component that covers the cost of building new electricity infrastructure in the province, maintaining existing resources, as well as providing conservation and demand management programs." Changes in GA are due to changes in HOEP. A lower HOEP triggers a higher GA in order to cover the additional payments to regulated generations. We are interested in investigating this relationship as well as assessing the effect of each generation on GA. The results are summarized in Tables 2.11 to 2.12. which present the results of GLS and Time-Series regressions on GA.

The present results are significant in at least two major respects. One is the reverse sign of the coefficients when comparing the result from Table 2.4 and Table 2.5 with the result from Table 2.11 and Table 2.12. The observed opposite sign of the coefficients[38] can be attributed to the complementary nature of GA and HOEP towards payments to long-term generators contacts. Since GA and HOEP are moving in opposite directions, it is not surprising to observe an opposite effect of generations' production on each of them. The second major result from this set of tables is the effect of the coal on both prices. The Coefficient of coal is mostly significant at 0.1% level in all model specifications and in all tables. As can be seen from the results, a one percentage point increase in production of electricity by coal increases HOEP and decreases the GA (by 10% to 13% in GLS and by 5.5% to 7.1% in the time-series regressions). In addition, the magnitude of the reduction in GA is greater than the magnitude of increase in HOEP. These differences can be explained in part by the cheap and already existing infrastructure of coal-fired generations. For example, a one percentage point increase in the production of electricity by renewable

[38]Although the sign of the estimated coefficients for each fuel type has not always changed when comparing the results in these tables, the general trend shows that different fuel types have opposite effect on the HOEP and the GA.

sources such as solar generations would require building the infrastructure, which essentially increases GA; however, if we increased the electricity production by employing the already existing coal-fired generations, we would not need to account for costs of building infrastructure. In addition, since coal is relatively less expensive, the more electricity production increases by engaging coal-fired generations, the more GA decreases.

2.7 Conclusion

The primary goal of this study is to assess the magnitude of effects of fuel mix on the HOEP and GA in Ontario. The implementation of the GEA in 2009 resulted in Ontario moving towards renewable energy sources in electricity and a shift away from utilizing coal-fired generation. Exploiting the changes in generation fuel mix resulting from the GEA offers some interesting identifying variation to estimate corresponding impacts with respect to electricity prices. Assessing such effects enables better prediction of future electricity prices as well as determining the most efficient combination of generations. Most of our analysis employs data from 2010-2013. This time period witnessed rather sharp changes in fuel mix, which went beyond the elimination of coal. Specifically, the proportion of electricity from nuclear and wind power increased substantially. Therefore, our unique dataset enables us to contribute to the literature by exploiting time-series variation generated by the GEA, to assess the effects of differences in fuel types on GA and HOEP during the coal phase-out period.

Since the data contain observations of multiple generations production over multiple time periods, we were able to form a panel dataset. We employed General Least Square (GLS) and Time-Series in a semi-log specification to investigate the effects of fuel mix. In tandem, our econometric results suggest that controlling for other factors, a one percentage point reduction in the proportion of coal relative to hydro is associated with a roughly 5% increase in the HOEP in recent years. The marginal effects of gas and nuclear based power are comparable. On the other hand, a one percentage point increase in wind based power is associated with almost a 10% decline in the HOEP, which is almost twice the marginal impact of other energy sources. But it is important to acknowledge that by the end of the studied sample, wind was roughly a bit more than 3% of total consumption.

It is important to extrapolate what these econometric results imply for the impacts that coal elimination has had. Based on the econometric regressions from the $2012-2013$ data the coefficient estimate of coal power is -0.047. Therefore, controlling for other factors the decrease in the proportion of coal over this time period from 3.56% to zero implies that the HOEP should have risen by approximately 2%. This effect should be amplified by the 8.7 percentage point decline in the proportion of gas (from 17.5% to 8.8%). However, nuclear power rose by 7.1 percentage points (from 57.7% to 64.8%), wind power increased by roughly 0.7 percentage points (from 1.89% to 2.59%), and hydro power rose from 18.4% to 23%. Basically, the increase in other sources of energy outweighed the effects of eliminating coal, which explains why the average HOEP fell from 26.4 $\$/MWh$ to 23 $\$/MWh$ (a drop of a little more than 11%)[39].

In contrast, the GA in terms of $\$/MWh$, rose by almost 50% from 42.64 $\$/MWh$ to 63.47 $\$/MWh$. Taking the more conservative estimates from the Time Series model, the econometric results imply that the 3.71 percentage point decrease in coal could be linked to a 24.3% (3.71 x -0.0657) increase in Global Adjustment per MWh. However, we are unable to confirm why this is exactly the case. A potential reason could be the shift to nuclear and wind power, with both sources having guaranteed rate long term impacts. The effects of nuclear power generation on GA could be attributable to the significant refurbishments of existing nuclear power plants. Future research will be devoted to understanding the driving factors behind these coefficient estimates. However, it is important to note the comparable coefficient estimates of coal and nuclear with respect to Global Adjustment. The implication is that the increase in wind power generation may not be exclusively responsible for rising Global Adjustment payments.

The HOEP has fallen over time, and any impacts from the elimination of coal have

[39] Based on authors' calculation, the distribution of fuel mix and the average HOEP and GA in 2012 (2013) are as follow: coal 3.56% (0.036%), gas 17.44% (8.78%), hydro 18.35% (23%), other 1.03% (0.23%), nuclear 57.71% (64.82%) wind 1.88% (2.58%), HOEP 26.4 (23.42) $\$/MWh$ and GA 42.64 (63.47) $\$/MWh$

been outweighed by a greater reliance on nuclear and wind. Of course, a lower HOEP from increased reliance on nuclear power generation comes at the cost of higher GA payments. However, the benefits from eliminating coal extend beyond implications for consumer electricity bills. Future research will focus on incorporating the health benefits associated with the elimination of coal.

2.8 Tables

Table 2.1: Summary Statistics (2009-2014)

Variable	Observation	Mean	Std. Deviation	Min	Max
HOEP	49656	30.25796	28.31026	-138.79	1891.14
GA	68	41.8344	16.9641	-0.27	78.55
Coal	49656	684.9861	893.5438	0	5103
Gas	49656	2181.334	1207.373	0	6882
Hydro	49656	3887.352	922.2005	0	6233
Nuclear	49656	9819.255	1033.984	0	12286
Other	49656	152.1841	78.46169	0	1638
Wind	49656	461.306	404.2114	0	2201
Total	49656	17186.42	2321.635	0	25836
Average Temperature	49656	2.9806	3.5866	-7.6652	12.0747
Average Relative Humidity	49656	23.7796	5.0143	5.586	32.8788
Exchange Rate	49656	104.4454	6.4362	95.53	126.4514
Unemployment rate	49656	8.1394	0.6534	7.3	9.6

Source: Authors' own calculation.

Table 2.2: Number of Incidents in which Value of the Variable reported as 0 (2009-2014)

Variable	**Number of Incidents**
HOEP	19
Coal	4703
Gas	1
Hydro	1
Nuclear	1
Wind	3
Total	1

Source: Authors' own calculation.

Table 2.3: HOEP Summary Statistics (2009-2014)

Month	Obs	Mean	Std.Dev	Min	Max
January	4464	39.75441	34.07248	-138.43	611.38
February	4056	40.85967	48.47652	-71.5	1891.14
March	4464	34.68504	40.27466	-128.18	529.37
April	4320	25.81066	21.14319	-138.79	410.7
May	4464	25.2414	24.14938	-128.12	583.71
June	4320	27.51395	24.43578	-128.23	535.28
July	4464	31.31075	23.71164	-128.05	492.89
August	4464	28.95612	21.82792	-128.64	382.64
September	3600	25.86867	20.18334	-108.51	475.05
October	3720	26.04756	19.1882	-128.13	544.87
November	3600	25.42108	16.41809	-128.08	232.92
December	3720	29.79927	15.4234	-128.12	196.63

Source: Authors' own calculation.

Table 2.4: GLS Regression of Natural Log of HOEP (2009-2014)

	Summary	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Coal	3.7170	0.0226***	0.0325***	0.0222***	0.0371***	0.0171***
	(4.5589)	(0.0040)	(0.0043)	(0.0026)	(0.0040)	(0.0041)
Gas	12.2449	0.0207***	0.0092***	-0.0023	0.0122***	-0.0025
	(5.5530)	(0.0033)	(0.0026)	(0.0035)	(0.0021)	(0.0026)
Nuclear	57.8506	-0.0356***	-0.0399***	-0.0497***	-0.0307***	-0.0352***
	(7.9108)	(0.0017)	(0.0019)	(0.0047)	(0.0030)	(0.003)
Other	0.8864	-0.0790*	-0.0777	-0.0185	0.0043	0.0218
	(0.3810)	(0.0378)	(0.0343)	(0.0332)	(0.0312)	(0.0252)
Wind	2.7081	-0.0565***	-0.0889***	-0.1001***	-0.0876***	-0.0951***
	(2.3464)	(0.0072)	(0.0097)	(0.0121)	(0.0099)	(0.01)
Total		NO	NO	NO	NO	0.00007***
						(6.61e-06)
Avg. Temp.		NO	-0.0394	NO	-0.0439	-0.0349***
			(0.0059)		(0.0067)	(0.0058)
Avg. Rel. Hum.		NO	0.0061	NO	0.0135	0.0118***
			(0.0021)		(0.0023)	(0.0023)
Exchange Rate		NO	YES	NO	YES	YES
Unemployment Rate		NO	YES	NO	YES	YES
Hour		NO	NO	YES	YES	YES
Day Of Week		NO	NO	YES	YES	YES
Month		NO	NO	YES	NO	NO
Year		NO	NO	YES	YES	YES
Constant		5.0751***	8.1306	6.8871***	7.2511***	6.1541***
		(0.1045)	(0.5253)	(0.3624)	(0.4716)	(0.4157)
Observation		49637	49637	49637	49637	49637
R^2		0.2162	0.2464	0.2942	0.2894	0.2967

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "hydro". Regressions are based on the hourly data from January 2009 to August 2014, however, Exchange rate and the Unemployment rate vary monthly.

Table 2.5: Time-Series Regression of Natural Log of HOEP (2009-2014)

	Summary	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Coal	3.7170	0.0049***	0.0125***	0.0079***	0.0178***	0.0002
	(4.5589)	(0.0009)	(0.0010)	(0.0015)	(0.0013)	(0.0014)
Gas	12.2449	0.0089***	0.00008	-0.0096***	0.0016	-0.0114***
	(5.5530)	(0.0009)	(0.0011)	(0.0015)	(0.0012)	(0.0014)
Nuclear	57.8506	-0.0307***	-0.0364***	-0.0.436***	-0.0288***	-0.0328***
	(7.9108)	(0.0010)	(0.0011)	(0.0018)	0.0014	(0.0014)
Other	0.8864	-0.0530***	-0.0601***	-0.0297**	-0.0088	0.0067
	(0.3810)	(0.0117)	(0.0110)	(0.0104)	(0.0100)	(0.0092)
Wind	2.7081	-0.0627***	-0.0877***	-0.0978***	-0.0875***	-0.0942***
	(2.3464)	(0.0026)	(0.0028)	(0.0028)	(0.0028)	(0.0029)
Total		NO	NO	NO	NO	0.00007***
						(2.64e-06)
Lag24HOEP		0.2425***	0.2311***	0.2129***	0.2154***	0.2127***
		(0.0124)	(0.0122)	(0.0122)	(0.0123)	(0.0122)
Lag25HOEP		0.1618***	0.153***	0.1393***	0.1403***	0.1398***
		(0.0117)	(0.0115)	(0.0117)	(0.0117)	(0.0116)
Avg. Temp.		NO	-0.0267***	NO	-0.0316***	-0.0238***
			(0.0008)		(0.0009)	(0.0009)
Avg. Rel. Hum.		NO	0.0049***	NO	0.0109***	0.0094***
			(0.0008)		(0.0008)	(0.0008)
Exchange Rate		NO	YES	NO	YES	YES
Unemployment Rate		NO	YES	NO	YES	YES
Hour		NO	NO	YES	YES	YES
Day of Week		NO	NO	YES	YES	YES
Month		NO	NO	YES	NO	NO
Year		NO	NO	YES	YES	YES
Constant		3.7293***	6.0568***	5.2006***	5.4243***	4.4690***
		(0.0821)	(0.1512)	(0.1327)	(0.2456)	(0.2405)
Observation		49579	49579	49579	49579	49579
Adjusted R^2		0.3369	0.3542	0.3739	0.3714	0.3772

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "hydro". Regressions are based on the data from January 2009 to August 2014 , however, Exchange rate and the Unemployment rate vary monthly.

Table 2.6: Time-Series Regression of Natural Log of HOEP (2010-2011)

	Summary	**Reg(1)**	**Reg(2)**	**Reg(3)**	**Reg(4)**	**Reg (5)**	**Reg (6)**
Coal	5.1641	0.0002	-0.0055***	-0.0052**	-0.0021	-0.0103***	-0.3205***
	5.4041	(0.0017)	(0.0019)	(0.0025)	(0.0024)	(0.0027)	(0.0819)
Gas	13.6716	0.0001	-0.0025	-0.0077***	-0.0006	-0.0061**	-0.2782***
	(5.3630)	(0.0016)	(0.0019)	(0.0025)	(0.0023)	(0.0024)	(0.0657)
Nuclear	56.8615	-0.0266***	-0.03***	-0.0351***	-0.0247***	-0.026***	-0.6298***
	(7.9598)	(0.0015)	(0.0017)	(0.0030)	(0.0027)	(0.0027)	(0.0603)
Other	0.8201	-0.0403***	-0.0457***	-0.0148	-0.0275**	-0.0354***	3.2327***
	(0.3537)	(0.0105)	(0.0112)	(0.0116)	(0.0120)	(0.0117)	(0.6845)
Wind	2.2689	-0.06428***	-0.0714***	-0.0661***	-0.0651***	-0.0678***	-1.3931***
	(1.9480)	(0.0051)	(0.0051)	(0.0051)	(0.0053)	(0.0054)	(0.0947)
Total		NO	NO	NO	NO	0.00002***	0.0017***
						(3.32e-06)	(0.0001)
Lag2HOEP		0.3247***	0.3219***	0.3214***	0.3227***	0.322***	0.23***
Lag3HOEP		-0.0008	-0.0011	0.0035	0.0029	0.0034	0.0238
Lag4HOEP		0.0444*	0.0442*	0.0485*	0.0482*	0.0485*	0.0296
Lag5HOEP		0.0342	0.0342	0.0377*	0.0375*	0.0379*	0.0182
Lag6HOEP		-0.0043	-0.0041	-0.0005	-0.0007	-0.0001	-0.0087
Lag7HOEP		-0.0419***	-0.0416***	-0.039**	-0.0392**	-0.0384**	-0.0109
Lag8HOEP		-0.0412***	-0.0412***	-0.0388***	-0.0388***	-0.0381***	-0.0185*
Lag9HOEP		0.0199*	0.0189*	0.0203*	0.0209*	0.022**	0.0112
Lag24AvgHOEP		0.0723***	0.0709***	0.0615***	0.0675***	0.0668***	0.1207***
Lag48AvgHOEP		0.0247*	0.0230	0.0202	0.0254*	0.0265*	0.0217
Avg. Temp.		NO	-0.0031***	-0.0174***	-0.0045***	0.0016	0.517***
			(0.0012)	(0.0045)	(0.0013)	(0.0016)	(0.0589)
Avg. Rel. Hum.		NO	0.0009	0.0018	0.0018	0.0003	-0.0234
			(0.0011)	(0.0013)	(0.0012)	(0.0012)	(0.0278)
Exchange Rate		NO	YES	NO	YES	YES	YES
Unemployment Rate		NO	YES	NO	YES	YES	YES
Hour		NO	NO	YES	YES	YES	YES
Day of Week		NO	NO	YES	YES	YES	YES
Month		NO	NO	YES	NO	NO	NO
Year		NO	NO	YES	YES	YES	YES
Constant		3.598***	2.1074***	4.1323***	2.1889***	1.1295***	-24.1296***
		(0.1427)	(0.2725)	(0.2349)	(0.3409)	(0.3638)	(7.9513)
Observation	17520	17520	17520	17520	17520	17520	17520
Adjusted R^2		0.317	0.3199	0.3272	0.3238	0.3254	0.3357

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the hourly data from January 2010 to December 2011, however, Exchange rate and the Unemployment rate vary monthly.

Table 2.7: Time-Series Regression of Natural Log of HOEP (2012-2013)

	Summary	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**	**Reg (6)**
Coal	2.2566	-0.0036	-0.0035	-0.0101***	-0.0007	-0.0468***	-0.8069***
	(2.2683)	(0.0025)	(0.0028)	(0.0039)	(0.0028)	(0.0032)	(0.1249)
Gas	12.5979	-0.0285***	-0.0332***	-0.0327***	-0.0253***	-0.049***	-0.8347***
	(5.8860)	(0.0021)	(0.0023)	(0.0036)	(0.0024)	(0.0024)	(0.062)
Nuclear	58.6631	-0.0542***	-0.058***	-0.0576***	-0.0443***	-0.0492***	-0.8857***
	(7.3083)	(0.0023)	(0.0026)	(0.0047)	(0.0031)	(0.0027)	(0.059)
Other	0.9487	-0.0012	-0.0090	-0.0066	0.0061	0.0033	6.8072***
	(0.2932)	(0.0172)	(0.0178)	(0.0182)	(0.0177)	(0.0162)	(0.9124)
Wind	3.2664	-0.0852***	-0.0923***	-0.0844***	-0.0809***	-0.0997***	-1.8041***
	(2.4470)	(0.0042)	(0.0044)	(0.0047)	(0.0044)	(0.0044)	(0.0849)
Total		NO	NO	NO	NO	0.0001***	0.0033***
						(6.21e-06)	(0.0001)
Lag2HOEP		0.4322***	0.4272***	0.4242***	0.4222***	0.4076***	0.193***
Lag3HOEP		0.0018	0.0011	0.0095	0.0074	0.007	0.00002
Lag4HOEP		-0.0203	-0.0207	-0.0110	-0.0124	-0.0119	0.05**
Lag5HOEP		0.0121	0.0113	0.0222	0.0209	0.021	0.009
Lag6HOEP		0.0128	0.0119	0.0219	0.0206	0.0219	0.0136
Lag7HOEP		-0.0128	-0.0138	-0.0055	-0.0066	-0.0043	0.018
Lag8HOEP		-0.0066	-0.0088	-0.0036	-0.0047	-0.0029	-0.0065
Lag9HOEP		0.0206**	0.0126	0.0117	0.0089	0.012	0.0048
Lag24AvgHOEP		0.1141***	0.1152***	0.096***	0.0993***	0.0906***	0.1709***
Lag48AvgHOEP		0.0645***	0.0599***	0.0452***	0.0454***	0.0474***	0.0075
Avg. Temp.		NO	-0.0034**	-0.0125***	-0.0033**	0.0055***	0.2316***
			(0.0014)	(0.0044)	(0.0016)	(0.0016)	(0.0617)
Avg. Rel. Hum.		NO	0.007***	0.0054***	0.0078***	0.0058***	0.0552
			(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0315)
Exchange Rate		NO	YES	NO	YES	YES	YES
Unemployment Rate		NO	YES	NO	YES	YES	YES
Hour		NO	NO	YES	YES	YES	YES
Day of Week		NO	NO	YES	YES	YES	YES
Month		NO	NO	YES	NO	NO	NO
Year		NO	NO	YES	YES	YES	YES
Constant		4.9302***	1.3603**	4.9466***	1.3131**	2.0624***	11.558
		(0.1760)	(0.5476)	(0.3263)	(0.5511)	(0.5388)	(14.0392)
Observation	17544	17506	17506	17506	17506	17506	17544
Adjusted R^2		0.4083	0.4127	0.4253	0.4245	0.4381	0.3094

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "hydro". Regressions are based on the hourly data from January 2012 to December 2013, however, Exchange rate and the Unemployment rate vary monthly.

Table 2.8: Time-Series Regressions of Natural Log of HOEP (Seasons of 2010-2011)

	W (%)	**Reg (W)**	**Sp (%)**	**Reg (Sp)**	**Su (%)**	**Reg (Su)**	**F (%)**	**Reg (F)**
Coal	6.1078	-0.0482***	5.0290	-0.0539***	7.2127	-0.0419***	2.3261	-0.0245***
	(5.4192)	(0.0065)	(5.7269)	(0.0081)	(6.1665)	(0.0062)	(1.8825)	(0.0074)
Gas	12.3320	-0.0454***	12.5653	-0.018***	15.3114	-0.0524***	14.4366	-0.0475***
	(5.1770)	(0.0059)	(5.0027)	(0.0068)	(5.7855)	(0.0054)	(4.8417)	(0.0079)
Nuclear	55.9495	-0.0678***	55.7601	-0.0535***	57.7164	-0.071***	57.9883	-0.0597***
	(5.9961)	(0.0065)	(7.5851)	(0.0081)	(10.1295)	(0.0078)	(7.2599)	(0.0074)
Other	0.8040	-0.1175***	0.8715	-0.0256	0.7406	-0.0326*	0.8644	-0.1912
	(0.1708)	(0.0272)	(0.3677)	(0.0215)	(0.5238)	(0.0192)	(0.2203)	(0.0522)
Wind	2.1981	-0.0671***	2.2051	-0.106***	1.4402	-0.1058***	3.2297	-0.1087***
	(1.7485)	(0.0086)	(1.8258)	(0.0136)	(1.2798)	(0.0142)	(2.3478)	(0.0112)
Total		0.00002**		0.00005***		-6.55e-06		0.00001
		(9.85e-06)		(0.00001)		(0.00001)		(0.00001)
Lag2HOEP		0.3481***		0.2878***		0.3356***		0.2885
Lag3HOEP		0.031		-0.0029		0.0839		-0.0364
Lag4HOEP		0.0456		0.041		0.0392		0.0446
Lag5HOEP		0.0273		0.1001**		-0.0173		-0.0284
Lag6HOEP		0.0006		-0.0051		-0.0299		0.0032
Lag7HOEP		-0.0405		-0.0643**		-0.0406		0.0023
Lag8HOEP		-0.0249		-0.0394		-0.0331		-0.0413***
Lag9HOEP		0.0419*		0.0173		0.0429		0.0001
Lag24AvgHOEP		0.0644*		0.0572**		0.0382		0.1341**
Lag48AvgHOEP		-0.0133**		0.0801***		0.014		-0.1603**
Avg. Temp.		-0.0375***		-0.0524***		0.0709***		-0.0266***
		(0.0093)		(0.01)		(0.0178)		(0.0087)
Avg. Rel. Hum.		0.0026*		0.0063*		0.0027		-0.0024
		(0.0014)		(0.0032)		(0.0022)		(0.0030)
Exchange Rate		YES		YES		YES		YES
Unemployment Rate		YES		YES		YES		YES
Hour		YES		YES		YES		YES
Day of Week		YES		YES		YES		YES
Year		YES		YES		YES		YES
Constant		7.1806***		10.6473		-4.6944***		11.6985**
		(1.1681)		(2.2846)		(0.746)		(5.9788)
Observation	4320	4320	4368	4368	4416	4416	4416	4416
Adjusted R^2		0.425		0.3264		0.4339		0.2718

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the hourly data from January 2010 to December 2011, however, Exchange rate and the Unemployment rate vary monthly. “W”, “Sp”, “Su” and “F” represent Winter (January, February and March), Spring (April, May and June), Summer (July, August and September) and Fall (October, November and December)

Table 2.9: Time-Series Regressions of Natural Log of HOEP (Seasons of 2012-2013)

	W (%)	**Reg (W)**	**Sp (%)**	**Reg (Sp)**	**Su (%)**	**Reg (Su)**	**F (%)**	**Reg (F)**
Coal	2.9244	-0.0776***	1.6412	0.0111	2.8780	-0.1142***	1.5869	-0.1066***
	(1.9733)	(0.0113)	(1.9885)	(0.0087)	(2.7819)	(0.009)	(1.8210)	(0.0118)
Gas	15.3944	-0.1167***	11.1827	-0.0383***	13.8667	-0.1124***	9.9781	-0.0948***
	(5.3722)	(0.0126)	(5.1984)	(0.0056)	(7.0614)	(0.0077)	(3.8114)	(0.0076)
Nuclear	54.15	-0.1063***	58.4359	-0.0487***	60.5982	-0.1079***	61.3899	-0.078***
	(6.2150)	(0.0122)	6.1674	(0.0070)	(8.1042)	(0.009)	(5.8297)	(0.0111)
Other	0.9122	0.0534	0.9276	-0.1396**	0.9764	-0.0749***	0.9779	-0.2094***
	(0.1618)	(0.0975)	(0.3001)	(0.0345)	(0.4314)	(0.0233)	(0.1933)	(0.0699)
Wind	3.9143	-0.14***	3.1983	-0.0707***	1.9058	-0.1841***	4.0572	-0.1405***
	(2.5313)	(0.0138)	(2.2477)	(0.0075)	(1.5077)	(0.0146)	(2.7063)	(0.0096)
Total		0.0001***		0.0001***		0.0001***		0.0002***
		(0.00002)		(0.00001)		(0.00001)		(0.00002)
Lag2HOEP		0.3624***		0.4249***		0.3846		0.3595
Lag3HOEP		-0.0446		-0.038		0.0134		0.0813
Lag4HOEP		-0.0614		-0.0465		0.0012		0.0517
Lag5HOEP		0.0098		0.0619*		0.0156		-0.0056
Lag6HOEP		0.088**		-0.0059		-0.0198		0.0188
Lag7HOEP		0.022		-0.0182		-0.0265		-0.0143
Lag8HOEP		-0.0028		0.0201		-0.0092		-0.0355**
Lag9HOEP		0.012		0.0198**		0.0155		-0.0073
Lag24AvgHOEP		0.0297		0.0629**		0.3403		0.0698***
Lag48AvgHOEP		0.0125		0.0408		0.0117		-0.0022
Avg. Temp.		-0.045***		-0.0395***		0.053***		-0.0145*
		(0.0111)		(0.0078)		(0.0156)		(0.0076)
Avg. Rel. Hum.		0.006		0.0009		0.0142***		0.0073**
		(0.0043)		(0.0022)		(0.0028)		(0.0028)
Exchange Rate		YES		YES		YES		YES
Unemployment Rate		YES		YES		YES		YES
Hour		YES		YES		YES		YES
Day of Week		YES		YES		YES		YES
Year		YES		YES		YES		YES
Constant		-2.8786*		-3.5755*		11.7755***		13.3926***
		(1.5242)		(1.8787)		(1.7939)		(1.9939)
Observation	4344	4344	4368	4368	4416	4416	4416	4378
Adjusted R^2		0.3956		0.3643		0.5336		0.5285

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the hourly data from January 2012 to December 2013, however, Exchange rate and the Unemployment rate vary monthly. “W”, “Sp”, “Su” and “F” represent Winter (January, February and March), Spring (April, May and June), Summer (July, August and September) and Fall (October, November and December)

Table 2.10: Time-Series Regressions of Natural Log of HOEP (Sensitivity Analysis)

	2010-2011		2012-2013	
	Reg (1)	**Reg (2)**	**Reg (3)**	**Reg (4)**
Coal	-0.0103***	-0.0103***	-0.0468***	-0.0468***
	(0.0034)	(0.0032)	(0.0056)	(0.0039)
Gas	-0.0061*	-0.0061**	-0.049***	-0.049***
	(0.0031)	(0.0028)	(0.004)	(0.0028)
Nuclear	-0.026***	-0.026***	-0.0492***	-0.0492***
	(0.0037)	(0.0032)	(0.0038)	(0.0031)
Other	-0.0354**	-0.0354**	0.0033	0.0033
	(0.0196)	(0.0139)	(0.0255)	(0.0194)
Wind	-0.0678***	-0.0678***	-0.0997***	-0.0997***
	(0.0066)	(0.0063)	(0.0066)	(0.0052)
Total	0.00002***	0.00002***	0.0001***	0.0001***
	(4.88e-06)	(3.97e-06)	(0.00001)	(7.32e-06)
Lag2HOEP	0.322***	0.322***	0.4076***	0.4076***
Lag3HOEP	0.0034	0.0034	0.007	0.007
Lag4HOEP	0.0485**	0.0485*	-0.0119	-0.0119
Lag5HOEP	0.0379*	0.0379*	0.021	0.021
Lag6HOEP	-0.0001	-0.0001	0.0219	0.0219
Lag7HOEP	-0.0384**	-0.0384**	-0.0043	-0.0043
Lag8HOEP	-0.0381**	-0.0381**	-0.0029	-0.0029
Lag9HOEP	0.022**	0.022**	0.012	0.012
Lag24AvgHOEP	0.0668**	0.0668**	0.0906***	0.0906***
Lag48AvgHOEP	0.0265	0.0265	0.0474*	0.0474**
Avg. Temp.	0.0016	0.0016	0.0055**	0.0055**
	(0.0021)	(0.0019)	(0.0026)	(0.0026)
Avg. Rel. Hum.	0.0003	0.0003	0.0058***	0.0058***
	(0.0018)	(0.0015)	(0.002)	(0.002)
Exchange Rate	YES	YES	YES	YES
Unemployment Rate	YES	YES	YES	YES
Hour	YES	YES	YES	YES
Day of Week	YES	YES	YES	YES
Month	NO	NO	NO	NO
Year	YES	YES	YES	YES
Constant	1.1295**	1.1295**	2.0624***	2.0624***
	(0.4838)	(0.4343)	(0.7624)	(0.7624)
Observation	17520	17520	17506	17506
Adjusted-R^2	0.3254	0.3254	0.4381	0.4381

Note: Standard errors are in parentheses and clustered at the day level in Reg (1) and Reg (3). Reg (2) and Reg (4) consider Newey-West standard error structure. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the hourly data, however, Exchange rate and the Unemployment rate vary monthly.

Table 2.11: Monthly OLS Regressions of Natural Log of GA

	Summary	Reg (1)	Reg (2)	Reg (3)	Reg (4)
Coal	3.7177	-0.1342***	-0.1097***	-0.1192***	-0.1251***
	(3.6863)	(0.0311)	(0.0279)	(0.0352)	(0.0401)
Gas	12.2491	-0.0234	-0.0809***	-0.0764**	-0.0728*
	(3.209)	(0.0248)	(0.0261)	(0.0309)	(0.0363)
Nuclear	57.8359	-0.0136	-0.0362	-0.0557	-0.0523
	(3.8472)	(0.0285)	(0.0299)	(0.0366)	(0.0461)
Other	0.8864	0.2039	0.1784	-0.6502	-0.5359
	0.1487	(0.5145)	(0.4604)	(0.5341)	(0.5833)
Wind	2.7116	-0.1181*	-0.0008	-0.0615	-0.1244
	(1.2724)	(0.0708)	(0.0875)	(0.0995)	(0.1172)
Total		NO	NO	NO	-0.00001
					(0.0001)
Avg. Temp.		NO	0.0562**	0.0556	0.3951***
			(0.0274)	(0.0462)	(0.1311)
Avg. Rel. Hum.		NO	0.018	-0.012	-0.0044
			(0.0378)	(0.0452)	(0.0606)
Exchange Rate		NO	-0.0483***	-0.0145	-0.0108
			(0.0116)	(0.0199)	(0.0201)
Unemployment Rate		NO	0.1373	0.4517*	0.4657*
			(0.1361)	(0.2406)	(0.2424)
Season		NO	NO	YES	YES
Month		NO	NO	YES	YES
Year		NO	NO	YES	YES
Constant		5.3099**	10.2712***	6.7999*	7.0177
		(2.1722)	(2.8418)	(3.8122)	(4.5674)
Observation		68	68	68	68
R^2		0.3101	0.5056	0.5513	0.5809

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the monthly data from January 2009 to August 2014.

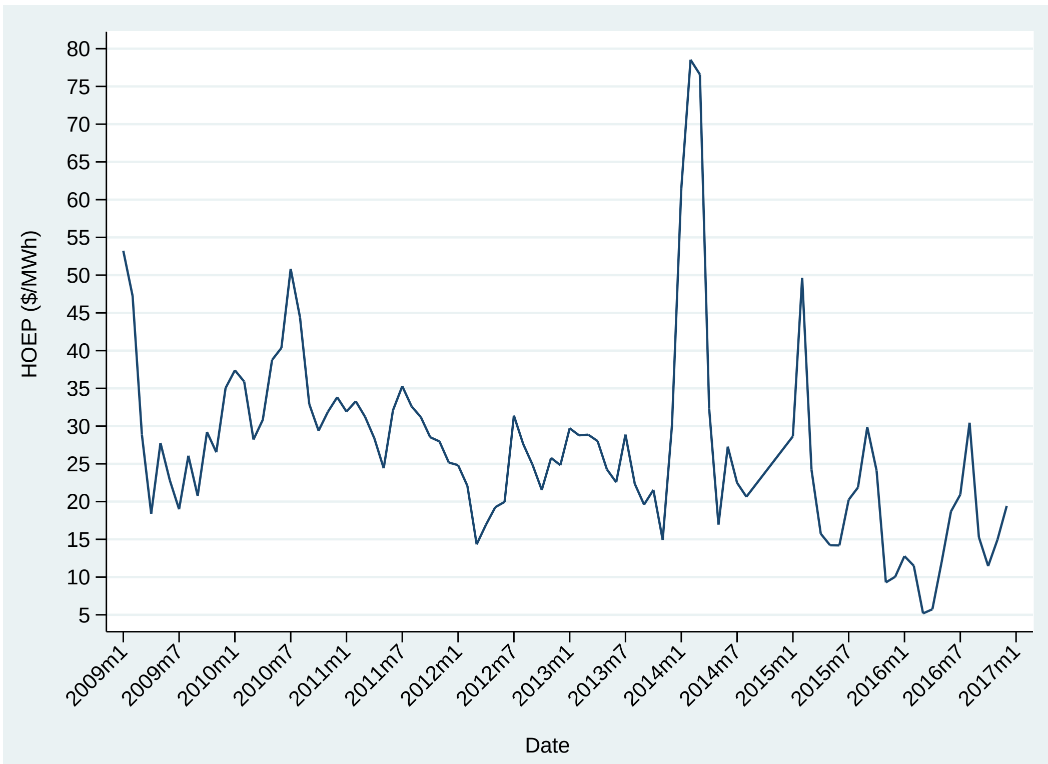
Table 2.12: Monthly Time-Series Regressions of Natural Log of GA

	Summary	Reg (1)	Reg (2)	Reg (3)	Reg (4)
Coal	3.7177	-0.0559**	-0.067**	-0.0719*	-0.0657**
	(3.6863)	(0.0208)	(0.0262)	(0.0276)	(0.0293)
Gas	12.2491	-0.0417***	-0.0754***	-0.0729***	-0.0683**
	(3.209)	(0.0133)	(0.0265)	(0.0248)	(0.0258)
Nuclear	57.8359	-0.0046	-0.0305	-0.028	-0.0276
	(3.8472)	(0.0181)	(0.0313)	(0.0364)	(0.0371)
Other	0.8864	0.1327	0.1938	-0.3712	-0.4503
	0.1487	(0.3175)	(0.3433)	(0.5577)	(0.5576)
Wind	2.7116	-0.0541	-0.0524	-0.0391	-0.0549
	(1.2724)	(0.0716)	(0.0812)	(0.0806)	(0.0851)
Total		NO	NO	NO	-0.00003
					(0.00004)
Lag1GA		0.3768**	0.2543*	0.1793	0.1819
		(0.1469)	(0.1416)	(0.1445)	(0.1443)
Avg. Temp.		NO	0.0269	0.0249	0.0151
			(0.0263)	(0.023)	(0.0275)
Avg. Rel. Hum.		NO	0.0329	0.0164	0.0168
			(0.0325)	(0.0319)	(0.0319)
Exchange Rate		NO	-0.0212*	-0.0053	-0.004
			(0.0124)	(0.0154)	(0.0154)
Unemployment Rate		NO	-0.0496	-0.0883	-0.0946
			(0.0629)	(0.1293)	(0.13)
Season		NO	NO	YES	YES
Year		NO	NO	YES	YES
Constant		3.3038**	7.3908**	6.5723**	7.1849**
		(1.3492)	(2.8508)	(2.5981)	(2.7647)
Observation		67	67	67	67
Adjusted R^2		0.4506	0.4775	0.5291	0.5214

Note: Robust standard errors are in parentheses. ***, ** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “hydro”. Regressions are based on the monthly data from January 2009 to August 2014.

2.9 Figures

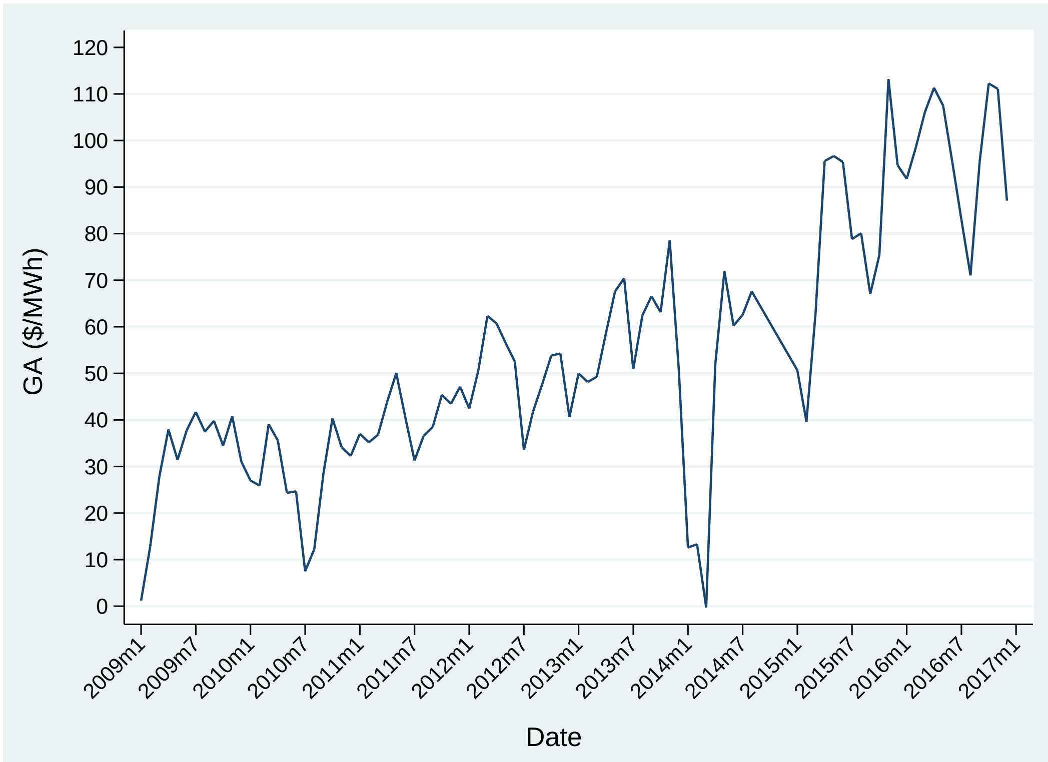
Figure 2.1: Average Monthly Hourly Ontario Energy Price (2009-2016)



Source: Authors' own calculation.

Note: The graph is based on the average monthly HOEP data and it excludes September 2014 to December 2014.

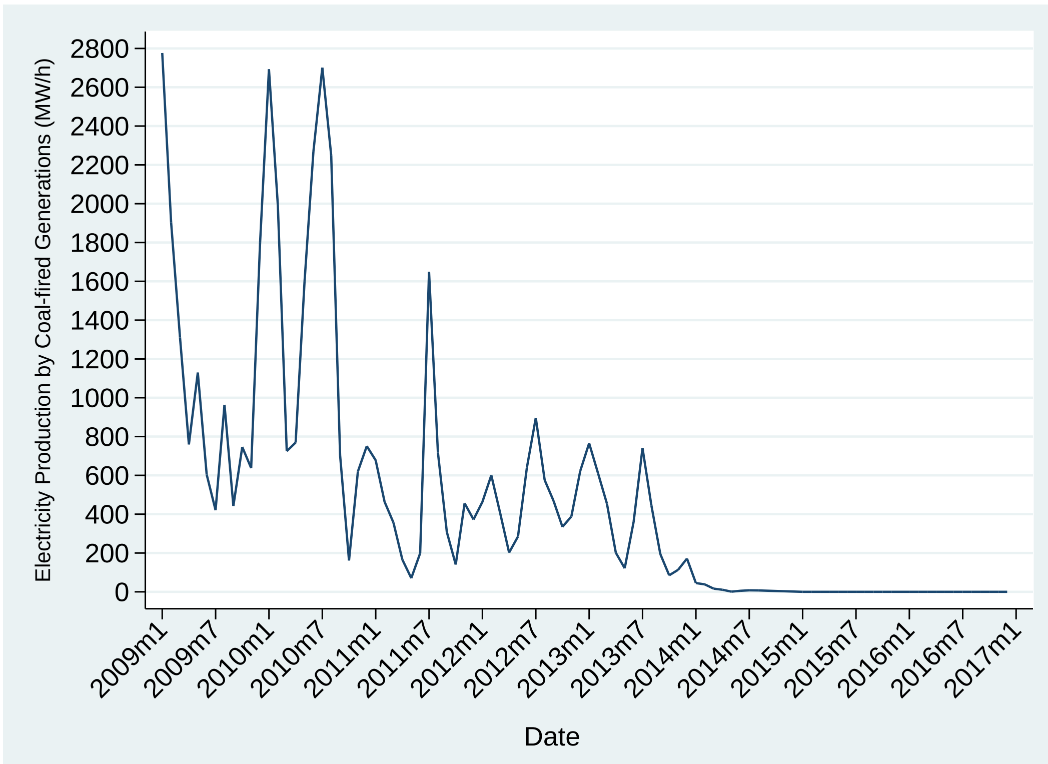
Figure 2.2: Monthly Global Adjustment (2009-2016)



Source: Authors' own calculation.

Note: The graph is based on the monthly GA data and it excludes September 2014 to December 2014.

Figure 2.3: Average Monthly Electricity Production by Coal-fired Generators (2009-2016)



Source: Authors' own calculation.

Note: The graph is based on the monthly average of coal-fired generations and it excludes September 2014 to December 2014.

Chapter 3

Estimating the Effects of Eliminating Coal-Fired Electricity Generation on Air Quality: Evidence from Ontario's Green Energy Act

3.1 Introduction

The Green Energy and Green Economy Act enacted by the Ontario government in 2009 was an ambitious policy aimed at shifting the province's electricity power generation to cleaner sources of energy. As a result, the government gave significant subsidies to different generators of renewable energy, such as wind and solar, and also committed to the elimination of coal-fired generating plants. This policy was motivated by research findings, which suggested that coal-fired plants in Ontario were emitting significant amounts of pollution. Perrotta (2002) notes results from previous studies, suggesting that in 2002, coal-fired plants in Ontario were responsible for: 23% of sulphur dioxide (SO_2) emissions and 14% of nitrogen oxide (NO_x) emissions that contributed to air pollution and acid rain; and 20% of the province's greenhouse gases emissions[1].

However, recent research has been critical of the Green Act. McKitrick and Aliakbari (2017) find small improvements in air quality that could be associated with the closure of coal-fired plants. They conclude that the same improvements in air quality could also have been achieved through the installation of new pollution control systems rather than the actual closure of the plants. Trebilcock (2017) notes that the policies associated with the Act have resulted in significant increases in electricity costs to consumers, with very limited environmental benefits and negligible economic growth. He also points to the large gap between fixed prices, which were promised to renewable energy producers through 20 year feed-in-tariff contracts, and actual wholesale prices[2].

As a result, it is unsurprising that electricity costs to consumers have increased quite significantly, As documented by Trebilcock (2017), in November 2016 the off-peak price of 8.7 cents per kwh was roughly double the corresponding price of 4.4 cents per kWh.

[1] "Ontarios Coal Plant Phase-out Produced Many Health and Environmental Benefits", by Kim Perrotta (2017), Executive Director, Canadian Association of Physicians for the Environment and available at, http://www.cela.ca/blog/2017-01-19/ontario-coal-plant-phase-out-produced-many-health-and-environmental-benefits.

[2] Trebilcock (2017) documents that the price for power from wind in 2009 was set at 13.5 cents per kwh and solar power producers could receive up to 80 cents per kilowatt hour through similar contracts. In contrast, the average total wholesale cost of electricity in the same year was around 6 cents per kilowatt hour.

Similarly, on-peak prices roughly doubled from 9.3 cents per kWh to 18 cents per kWh over the same time period, with mid peak prices also jumping from 8 cents per kWh to 13.2 cents per kWh. From another perspective, Dachis, Jacobs, and Muthukumaran (2016) find that electricity in Ontario in 2006 was 40% cheaper than in western New York State. However, by 2015, Ontarios electricity prices became 5% higher than those prevailing in western New York (State). The upward trend in electricity prices will persist. The Ontario government's recent decision to reduce electricity bills through the elimination of the Harmonized Sales Tax will simply shift the financial burden to future generations as the policy has been financed through increased government debt and will therefore also add significant interest costs (Trebilcock [2017]).

There are other contributing factors towards higher electricity bills in Ontario. Sen [2015] points to the costs of nuclear plant refurbishment, new transmission and distribution infrastructure, the impacts of new peak-period-supplying power plants coming online, as well as the legacy costs of Ontario Hydros debt. While it is true that electricity rates charged to consumers on a per kWh basis have significantly increased and resulted in higher bills for consumers with rising consumption, overall electricity demand in Ontario have in fact declined. Much of the above costs have also been covered through increases in the Global Adjustment, which is a charge passed directly onto retail consumers, and is the difference between market driven wholesale prices and guaranteed prices to generators. Sen [2015] finds that from 2006 to 2014, total GA charges in Ontario increased from $654 million to $7 billion, while in comparison, total HOEP costs to all customers over the same time period have correspondingly declined from over $7 billion to roughly $5 billion .

The appropriate policy question is whether the increase in total Global Adjustment charges driven by subsidies to renewables, have to some extent been offset by better air quality from the phase out of coal-fired plants and increased reliance on cleaner sources of energy. Answering this question is of relevance to Canadian public policy and to other jurisdictions as well. Specifically, the Federal Government recently announced a plan to eliminate all remaining coal-fired plants by 2030 [3] [4]. From a more global viewpoint, coal provides roughly 40% of the world's electricity, with much higher proportions in developing countries. Emissions from coal-fired plants contains significant pollutants that have been linked to adverse health outcomes. Therefore, additional evidence in this respect, is of obvious value. Ontario is the first North American jurisdiction to phase out coal-fired plants from its electricity system. This is all the more remarkable, given Ontarios prior reliance on coal electricity. In 2003, almost 25% of Ontarios electricity came from coal and the Nanticoke plant was North Americas largest coal-fired plant. Hence, the Green Act is a unique policy experiment offers credible identification and provides an opportunity to study empirically the significance of corresponding environmental benefits.

This study matches hourly level data on the fuel mix of electricity supply in the province to corresponding measures of air quality in the cities of Toronto, Hamilton, Ottawa, and Sarnia from 2009 to 2016, which allows us to estimate the effects of the declining share of coal power generation over a period in which coal generated power was slowly but completely eliminated. Employing data across different cities is an important sensitivity analysis which allows an assessment on whether any regression results reflect the effects of unobserved city specific characteristics. This study focuses specifically on changes in fuel mix on city levels of Ozone (O_3), Nitrogen Oxide (NO_x), and Particulate Matter ($PM_{2.5}$) - all of which have been linked to emissions from coal-fired plants. The paper also estimates the impacts of fuel mix on the probability of smog days.

Broadly speaking, there are similarities in regression results across cities. On average, increases in nuclear and wind powered generation (relative to lower coal) are significantly correlated with lower levels of Nitrogen Oxide (NO_x), and Particulate Matter ($PM_{2.5}$) in most cities. Higher levels of gas and hydro power are sometimes associated with lower levels of these pollutants, but their coefficient estimates are not consistently significant across

[3] For further information please refer to:
https://beta.theglobeandmail.com/report-on-business/industry-news/energy-and-resources/ottawa-to-announce-coal-phase-out-aims-for-virtual-elimination-by-2030/article32953930/?ref=http://www.theglobeandmail.com&

[4] For further information please refer to: http://www.cela.ca/blog/2017-01-19/ontario-coal-plant-phase-out-produced-many-health-and-environmental-benefits.

specifications. More nuclear power is correlated with lower Ozone (O_3) but increases in wind generated energy are counter-intuitively associated with more Ozone (O_3) in all cities.

3.2 Literature Review

Unfortunately, the relevant literature is thin. No other jurisdiction has completely phased out coal-fired plants in an attempt to reduce harmful emissions. There has been some research, which has looked at the effects of alternative strategies to mitigate carbon emissions. For example, the past few years have witnessed an increasing interest in the use of carbon capture and storage (CCS) facilities that can be coupled to coal-fired power plants. These facilities enable the continued use of fossil fuels while reducing carbon dioxide (CO_2) emissions, specifically by capturing harmful emissions and transporting them to a storage facility where they will be deposited and not released to the atmosphere. However, a 2013 consultation by the European Commission suggests that such technology has not evolved to a stage where it is a cost-effective solution to mitigating fossil fuel emissions[5]. Another example is the study done by Brown et al. [2017] on Alberta's electricity market. They investigate the effects of different forms of carbon pricing on wholesale electricity prices, output, and emissions in the short-run in Alberta and discuss how these effects depend on the market structure. The authors find that regardless of the degree of market competition, the output-based subsidy has a larger effect on prices and emissions than increasing the per tonne carbon price.

Chan et al. [2017] study the effects of restructuring of wholesale and retail electricity markets in the U.S. that began from the mid nineteen-nineties onwards, by using a panel data of coal-fired generating plants from $1991 - 2005$. While there are studies, which have investigated the effects of industry restructuring on different types of electricity plants (for example, Douglas [2006], Fabrizio et al. [2007], and Zhang [2007]), this paper is unique given the long time period of the sample, exclusive focus on coal-fired plants, and attempt

[5]The results of the consultation are available at, https://ec.europa.eu/energy/en/topics/oil-gas-and-coal/carbon-capture-and-storage. For further details please refer to Hammond and Spargo (2014).

to quantify unintended environmental effects. The authors find that deregulation induced efficiency improvements and reductions in coal costs, resulted in combined cost savings of nearly 15 percent of an average plants operating expenses. Further, these changes resulted in emissions reductions of 7.5%. However, this paper does not investigate the effects on local air quality. Linn et al. [2014] also focus on efficiencies by employing a unique panel data set of coal-fired generation units for the years 1985−2009. Their data includes monthly fuel input, generation, and coal prices by generation unit for nearly all U.S. coal plants. Their identification strategy is based on changes in coal prices. Their results indicate that a 10% increase in coal prices causes a 0.1% − 0.4% improvement in efficiency (electricity production per ton of coal). As is the case with Chan et al. [2017] this study does not estimate the corresponding effects on environmental quality.

Some recent studies estimate environmental benefits generated from cheaper natural gas that can be attributed to increased fracking. These papers are comparable to this study as they exploit changes in fuel mix. Holladay et al. [2016] build an hourly panel of fuel type, electricity output, and pollution emissions for every generator in the five boroughs of NYC from 2005-2010 and use the identification offered by the switch from oil to natural gas fired generators to estimate the corresponding effects on pollution emissions of New York City power plants. Their results suggest that the switch to cheaper natural gas can be associated with roughly a 2/3 reduction in SO_2 emissions. Holladay and LaRiviere [2017] estimate marginal CO_2 emissions for eight regions across the U.S. from 2006-2011. Their results suggest significant heterogeneity in reductions in CO_2 emissions across regions. In terms of research that has investigated the environmental benefits of renewable sources of energy, Cullen [2013] uses data on output from wind based (and other) generators for every 15 minutes from April of 2005 through April of 2007. The results showed that one MWh of wind power production offsets less than half a ton of CO_2, almost one pound of NO_x, and no discernible amount of SO_2. In summary, the results imply that the value of emissions offset by wind power exceed the cost of renewable energy only when the social costs of pollution are very high. Novan [2015] also employs data from Texas (from January 1, 2007 through December 31, 2011) and finds that while nontrivial amounts of emissions are avoided through the use of more wind, the marginal external benefits from wind powered generation are very different from other renewable sources, such as solar energy. This heterogeneity in marginal external benefits implies that policies that fail to acknowledge such differences result in less than first best outcomes.

In summary, while there are papers that have either looked at the effects of emissions reductions from generators as a result of increased reliance on natural gas or wind power, we have been unable to find a peer reviewed published study that has econometrically identified the effects of a reduced reliance on coal, or alternatively, an increased dependence on cleaner sources of electricity on local city level air quality. The only paper we are aware of that has specifically estimated the environmental effects of reduced reliance on coal-fired generation is McKitrick and Aliakbari (2017)[6]. They employ month level data from May 2004 to December 2014 for Hamilton, Toronto, and Ottawa and study the effects of reduced coal reliance on city levels of particulates ($PM_{2.5}$, or particulate matter smaller than 2.5 microns), nitrogen oxides (NO_x) and ground-level ozone (O_3). Their results suggest that the elimination of coal was associated with some reduction in average urban $PM_{2.5}$ levels but not in Toronto or Hamilton. The results with respect to other pollutants is not conclusive. The problem with this approach is that relying on monthly data hides a significant amount of the identifying variation available from hourly changes in fuel mix. Further, the study does not attempt to assess the effects of other types of fuel mix (such as nuclear energy) that also benefited from long term guaranteed contracts. Our paper attempts to contribute to the literature by exploiting hourly changes in fuel mix over time, which allow us to investigate the relative impacts of coal-fired, nuclear, and gas generated electricity on local city level pollution. This is a departure from most U.S. based studies that have focused on emissions emitted from specific generators.

3.3 Data

The dataset for this study contains hourly air pollutant data associated with downtown Toronto, Hamilton, Ottawa and Sarnia. The pollution data are obtained from the Ontario

[6]Available online at, https://www.fraserinstitute.org/studies/did-the-coal-phase-out-reduce-ontario-air-pollution

Ministry of the Environment and Climate Change for the period of 2009 – 2016[7]. This study is based on three type of air pollutants: (1) NO_x, (2) O_3 and (3) $PM_{2.5}$. In chemistry, NO_x refers to nitrogen dioxide (NO_2) and nitric oxide (NO) gases that can cause smog and acid rain. Furthermore, under specific weather conditions such as high temperature and reactions with other chemicals such as sulfur dioxide, NO_x can form ground level ozone (O_3) and particulate matter (PM)[8]. In addition, NO_x has the potential of burning lung tissue, exacerbating asthma, and rendering people more susceptible to chronic respiratory diseases[9]. Particulate matter ($PM_{2.5}$) can cause chronic bronchitis, aggravated asthma, and premature death, as well as resulting in reduced visibility. Therefore the focus of this study is on the three pollutants of NO_x, O_3 and $PM_{2.5}$. Table 3.3 gives a detailed summary statistics of pollutants, temperature and relative humidity in each year and each city over the sample period.

Figure 3.1 to 3.12 give some idea of the monthly average of each pollutant over 2009 – 2016 in the four cities of Toronto, Hamilton, Ottawa and Sarnia. With the exception of Ottawa, NO_x emissions (Figure 3.1, 3.4, 3.7 and 3.10) are generally declining through the sample period in all cities. However, NO_x emissions are clearly lower after the elimination of coal in 2014. O_3 emissions trend (Figure 3.2, 3.5 and 3.11) are mainly constant over the sample period in most cities. However, they do seem to dip in 2016. There is a clear upward trend in $PM_{2.5}$ (3.3 and 3.6) until 2014 in Toronto and Hamilton, after which there is a perceptible downwards shift. In Sarnia, however, The $PM_{2.5}$ is generally declining over the sample period and shows a more sharp decline in 2014.

Data on hourly electricity generation from coal, gas, hydro, nuclear, wind and other (solar and biofuel) type of power plants for the period of January 2009 to December 2016 were obtained from the Independent Electricity System Operator (IESO). By focusing on 2009 to 2016 we can estimate the effects of declining share of coal in electricity generation system on these specific measures of air quality. In addition, monthly exchange and

[7]Available online at, http://www.airqualityontario.com/history/

[8]For further details please refer to: http://www.icopal-noxite.co.uk/nox-problem/nox-pollution.aspx

[9]This description of pollution effects are taken from http://www.ucsusa.org/clean-energy/coal-and-other-fossil-fuels/coal-air-pollution#.Wce9f2hSzcs

unemployment rate were also downloaded form Statistics Canada website and used in our analysis to reflect general economic activity in Ontario.

In 2003, coal constituted roughly 25% of total Ontario power mix[10]. However, the proportion of coal in electricity fuel mix began to drop significantly after that. As can be seen in Table 3.2, coal power was roughly 8% in 2010 before dropping to 0.89% in 2014 when the phase out was complete. Over the same time period, the proportion of nuclear power rose from approximately 56% to 61.2% and wind grew from 1.9% to almost 4%. This increase in wind and nuclear power was accompanied by a corresponding decline in the other types of fuel (aside from coal). Table 3.1[11] gives the timeline in which coal was phased out in terms of the specific plants and the corresponding loss in capacity (MW).

The key identification for our study is the drop in coal generation from Nanticoke in 2011 and the complete phasing out of Nanticoke and Lambton by 2013. Nanticoke is 129 km from Toronto, while Lambton (Sarnia) is roughly 290 km west of Toronto. Lakeview was powered down in 2012 and converted to North America's largest purely biomass-fueled power plant[12]. Thunder Bay was shut down in April 2014 and converted to run on advanced biomass (wood pellets) and recommissioned on February 9, 2015[13]. Nanticoke and Lambton were decommissioned in 2013[14] [15].

3.4 Empirical Model

The purpose of this study is to examine the effects of electricity supplied by different sources of energy on three pollutants of ground-level ozone (O_3), fine particulate matter ($PM_{2.5}$)

[10]For further details please refer to: http://www.energy.gov.on.ca/en/archive/the-end-of-coal/

[11]Available at, http://www.energy.gov.on.ca/en/archive/the-end-of-coal/

[12]For more information please visit: http://www.ediweekly.com/largest-biomass-power-plant-na-set-open-atikokan/

[13]For more information please visit: http://www.opg.com/generating-power/thermal/stations/thunder-bay-station/Pages/thunder-bay-station.aspx

[14]For more information please visit: https://www.thespec.com/news-story/5738344-power-plant-s-closure-spells-end-of-era-for-nanticoke/

[15]For more information please visit: http://www.theobserver.ca/2016/11/22/lambton-generation-station-to-be-decommissioned.

and nitrogen oxide (NO_x) for the duration from January 2009 to December 2016. The nature of the data in this study enables us to adopt two approaches in order to evaluate the magnitude of such effects. In the first approach, we structure the data in a Panel format and run the Generalized Least Square (GLS) estimation in which the random effect of hours is captured. Random effects of hours is used to consider both the within and between variations in each hour. In our second approach, we estimate the model when we focus on the Time-Series nature of the data. The results of a Dickey-Fuller test for unit roots are presented in the appendix of this paper (Table C.1 to C.9). Upon rejection of the null hypothesis that the series contain a unit root, we consider the third and sixth lagged values of each dependent variable. This helps us to investigate the short-term effects of previous values on current values of air pollution. Considering the same set of independent variables in both approaches, we were able to compare the ability of the proposed models in explaining the relationship between different types of generations and each considered pollutant. Thus, the first model reads as follow:

$$NO_{x_{it}} = \beta_0+\beta_1 G_{it}+\beta_2 H_{it}+\beta_3 N_{it}+\beta_4 O_{it}+\beta_5 W_{it}+\beta_6 Total_{it}+\beta_7 Temp_{it}+\beta_8 Rel.Hum_{it}+ Y + S + DW + H + \varepsilon_{it}$$

$$O_{3_{it}} = \beta_0+\beta_1 G_{it}+\beta_2 H_{it}+\beta_3 N_{it}+\beta_4 O_{it}+\beta_5 W_{it}+\beta_6 Total_{it}+\beta_7 Temp_{it}+\beta_8 Rel.Hum_{it}+ Y + S + DW + H + \varepsilon_{it}$$

$$PM_{2.5_{it}} = \beta_0 + \beta_1 G_{it} + \beta_2 H_{it} + \beta_3 N_{it} + \beta_4 O_{it} + \beta_5 W_{it} + \beta_6 Total_{it} + \beta_7 Temp_{it} + \beta_8 Rel.Hum_{it} + Y + S + DW + H + \varepsilon_{it}$$
(3.1)

In the Panel dataset:

i = The Panel ID or Panel Variable which are the 24 hours of a day (i.e., 1,...,24);

t = The Panel's Time Variable for duration from 1st of January 2009 to 31st of December 2016 (i.e., date);

$NO_{x_{it}}$, $O_{3_{it}}$ and $PM_{2.5_{it}}$ are the amount of nitrogen oxide (in parts per billion (ppb)), ground-level ozone (in parts per billion (ppb)) and fine particulate matter (in microgram per cubic metre (mg/m^3)) in the air in hour i at time t, respectively;

G_{it},H_{it},N_{it},O_{it} and W_{it} are the percentage of electricity generated by gas, hydro, nuclear, other (such as solar and biofuel) and wind energy in hour i at time t respectively;
$Total_{it}$ is the total electricity produced (in megawatts (MW)) in hour i at time t;
$Temp_{it}$ and $Rel.Hum_{it}$ are the average temperature (in degrees Celsius $°C$) and relative humidity (in percentage) in hour i at time t.
Y, S, DW and H are dummy variables that capture the fixed effect of year, season, day of week and hour[16];
ε_t is an idiosyncratic error term.

Since we estimate the three above mentioned equations when the fuel mix are reported as percentages of total electricity supplied each hour, we have to omit one of the fuels to avoid collinearity. We drop coal from all regressions. Therefore, the coefficient estimates of different types of fuel reflect either the parts per billion (ppb) or microgram per cubic metre (mg/m^3) change in pollutants in response to a one percentage point increase in electricity generated by different sources of energy relative to coal. We also consider the total amount of electricity generated in each hour (in MW) to capture the overall hourly effect of electricity production on hourly pollution levels.

Using the GLS model when we consider the fixed effects of year, season, day of week and hour, it is possible to control for characteristics within each group that might affect the left-hand side variable (pollutant). Year fixed-effects are relevant to consider since under different situations such as uncontrolled weather conditions (wind speed or amount of precipitation[17]) in each year, the fuel mix would vary. The evidence of season fixed-effect is obvious from figures 3.1 to 3.12 [18]. Also, the possible differences between weekday and weekends air pollution due to low volume of business and different commuting pattern on weekends rationalizes the need for considering the day of week fixed-effect in this model. In addition, we controlled for the fixed effect of daily fluctuations in pollutants by considered quarter day dummies in our analysis. Hourly temperature and relative humidity are

[16]We divided the 24 hours of a day into 4 time intervals: 1) from midnight to 6AM, 2) 6AM to noon, 3) noon to 6PM, 4) 6PM to midnight. Therefore we considered 4 hour dummies rather than 24.

[17]The data for hourly precipitation and wind speed in these four cities are not available.

[18]Although the effect of season is more apparent in the O_3 and NO_x, we controlled for season fixed-effects in all regressions.

considered to control for the effect of weather condition on the production of electricity by different types of energy such as wind, hydro and other (like solar).

In the second model we focus on Time-Series nature of the dataset. We evaluate the effect of electricity produced by each source of energy on pollutants through the following reduced form specification:

$NO_{x_t} = \beta_0 + \beta_1 G_t + \beta_2 H_t + \beta_3 N_t + \beta_4 O_t + \beta_5 W_t + \beta_6 Total_t + \beta_7 NO_{x_{t-3}} + \beta_8 NO_{x_{t-6}} + \beta_9 Temp_t + \beta_{10} Rel.Hum_t + Y + S + DW + H + \varepsilon_t$

$O_{3_t} = \beta_0 + \beta_1 G_t + \beta_2 H_t + \beta_3 N_t + \beta_4 O_t + \beta_5 W_t + \beta_6 Total_t + \beta_7 O_{3_{t-3}} + \beta_8 O_{3_{t-6}} + \beta_9 Temp_t + \beta_{10} Rel.Hum_t + Y + S + DW + H + \varepsilon_t$

$PM_{2.5_t} = \beta_0 + \beta_1 G_t + \beta_2 H_t + \beta_3 N_t + \beta_4 O_t + \beta_5 W_t + \beta_6 Total_t + \beta_7 PM_{2.5_{t-3}} + \beta_8 PM_{2.5_{t-6}} + \beta_9 Temp_t + \beta_{10} Rel.Hum_t + Y + S + DW + H + \varepsilon_t$
(3.2)

Where:

t represents hours of the day from 1st of January 2009 to 31st of December 2016.

The focus of this study is on estimating β_1 to β_5 which yields the amount of change in air pollution (either in terms of *ppb* or mg/m^3) in response to a one percentage change in the electricity produced by different types of energy sources (relative to coal) in each hour. We run both regressions when we consider the dependent (air pollutants) and weather variables (temperature and relative humidity) in the four cities of Toronto, Hamilton, Ottawa and Sarnia.

Further, we look at the air quality in Ontario based on the smog advisories that are issued since 2009. In particular, we are interested to match the likelihood of smog advisory issued in Ontario to the production of electricity by different sources of energy. In this regressions we averaged the data at the daily level and then we estimated the following probit regression:

$Temp_t$ and $Rel.Hum_t$ are the average temperature and relative humidity in day t respectively.

$ExchangeRate$ is the Canadian monthly cents per United States dollar spot rate.

$UnemploymentRate$ the unemployment rate in Ontario that is seasonally adjusted for prime aged adults.

Y and M are sets of dummy variables for year and month respectively.

ε_t is an idiosyncratic error term.

In this model we consider Exchange and Unemployment rate to account for economic activities that might impacted the business, change the supply and increase the likelihood of smog days. We do not consider the Exchange and Unemployment rate with month dummies in the same regression. This is because both Exchange rate and Unemployment rate vary monthly and incorporating them with month dummies would lead to over-specification in month effects.

Before controlling for time-invariant variables that might affect the model (i.e., using time-specific fixed-effects), it was important to run the basic regression model within each defined model without considering any dummy variables on the pooled data for comparison purposes. The following section discusses the results of both the GLS and Time-series model in addition to the proposed Probit model.

This study is limited by the lack of information on the amount of electricity generated from different types of fuel mix in each city. In addition, there are many other variables that contributes to air pollution such as fumes from car exhausts and emissions from industries and manufacturing activities. Therefore, we might have an endogeneity problem which arises from the omitted variables. In this regard, we acknowledge the fact that the calculated coefficients might be upward biased.

3.5 Empirical Results

3.5.1 The effects of changing fuel mix on pollution

This section presents the findings of the research. Our study estimates the effects of hourly changes in fuel mix on Nitrogen Oxide (NO_x), Particulate Matter ($PM_{2.5}$), and ground level Ozone (O_3). Table 3.4 to 3.27 contain regression results of the effects of changes in the proportion of fuel mix with respect to each pollutant that are based on hourly data in Toronto, Hamilton, Ottawa and Sarnia. The benefits of hourly data are the availability of more identifying variation that is otherwise supressed through monthly averages. Each of these tables are organized similarly with estimates in all columns based on the GLS model (equation 3.1) except the last column which represents the result from the time-series model (equation 3.2). Columns (1) consists of results obtained after employing a wide array of covariates and after that each column consists of results further conditioned on different time fixed effects.

The estimates in Tables 3.4 to 3.9 show the results that are based on hourly data in Toronto. With respect to NO_x (Table 3.4), coefficient estimates of the proportion of nuclear and wind (whenever significant) are all negative. In contrast, coefficient estimates of gas, hydro and other fuel sources are positive and sometimes significant. Estimates in column (4) when we control for different time fixed effects, indicates that a one percentage point increase in wind (gas) relative to coal is associated with roughly a 0.97 (0.13) drop (increase) in NO_x. Coefficient estimate of temperature (relative humidity) in all columns are negative (positive) and statistically significant.

Coefficient estimates of fuel mix are statistically significant with respect to O_3, in Table 3.5. However, there are differences in signs as well as the magnitude of coefficient estimates. Coefficient estimates of nuclear power are negative and statistically significant at the 1% level, ranging from -0.37 to -0.06. Coefficient estimates of gas and hydro are also negative and statistically significant at the 1% level across all columns, with values from -0.34 to -0.03 and -0.19 to -0.04, respectively. Wind power is also statistically significant (at the 1% level), but with positive coefficients. An increase in the proportion of other power is also significantly associated (at varying levels of significance) with higher levels of O_3. Higher temperature is associated with higher ozone levels (at the 1% level), while an increase in relative humidity is correlated with lower ozone levels (at the 1% level).

Table 3.6 contains estimates with respect to $PM_{2.5}$. With the exception of other sources, an increase in the proportion of all other sources of electricity relative to coal (when statistically significant) is associated with a decline in $PM_{2.5}$ levels when we started to account for the fixed effects of time (column (2) to (5)). Coefficient estimates of nuclear energy are negative and significant (at 1%) in column (1) to (4) with coefficient estimates from -0.07 to -0.03 (from column (2) to (4)). A one percentage point increase in the proportion of wind generated energy is associated with roughly a 0.15 mg/m^3 decline in $PM_{2.5}$ levels (column (4)). A one percentage point rise in hydro power generation is associated (at the 1% level) with roughly a 0.04 mg/m^3 decline in $PM_{2.5}$ (column (4)). An increase in temperature and relative humidity is associated with increased levels of $PM_{2.5}$.

In summary, the empirical results do indicate that an increase in nuclear and wind generated power at the expense of coal is consistently associated with lower overall pollution levels. More wind generated power is associated with increased levels of ozone, but are correlated with significantly lower levels of NO_x and somewhat reduced $PM_{2.5}$. The coefficient estimates and summary statistics can be used to understand the magnitude of marginal effects. Take the case of NO_x. Coefficient estimates from column (4) imply that a one percentage point increase in nuclear power relative to coal is associated with a roughly 0.01 *ppb* decline in NO_x. Therefore, a 5.6 percentage point rise in the proportion of nuclear power is linked with a 0.056 drop in NO_x, controlling for all else. With a NO_x sample mean of 17.71 *ppb*, this is equivalent to a 0.32% decline in NO_x. However, the marginal effects of an increase in wind power are much larger. On average, a one percentage point increase in wind power generation is associated with a 0.97 *ppb* reduction in NO_x. This is a substantial 24.61% reduction in NO_x levels given its sample mean of 17.71 *ppb*. This is important given 4.5 percentage point increase in the proportion of wind powered generation over the sample period (from 1.55% in 2009 to 6.10% in 2016).

In contrast to NO_x, an increase in nuclear powered energy at the expense of coal is associated with larger marginal impacts with respect to reductions in O_3 levels (Table 3.5). A one percentage point rise in nuclear power is significantly associated with roughly a 0.16 *ppb* drop in O_3 levels. Hence, a 5.6 percentage point increase in nuclear power is correlated with an almost 0.9 *ppb* reduction in O_3 levels. Given that the sample mean of O_3 is roughly 26 ppb, this works out to a 3.46% decline in O_3 levels.

The effects of changes in fuel mix from $2009-2016$ on $PM_{2.5}$ (Table 3.6) have also been pronounced. A one percentage point increase in nuclear power is significantly associated with an approximately 0.03 drop in $PM_{2.5}$. Therefore, a 5.6 percentage point rise in nuclear power generation corresponds to a 0.16 $PM_{2.5}$ reduction. Based on a $PM_{2.5}$ sample mean of roughly 7, this is equivalent to an almost 2.39% decline in hourly $PM_{2.5}$ levels. The largest impact comes from wind power with a coefficient estimate of almost -0.15. The 4.5 percentage point increase in wind power over the sample period is then equivalent to a 0.67 mg/m^3 reduction in $PM_{2.5}$, which is equivalent to an almost 9.5% decline in $PM_{2.5}$ levels.

While Tables 3.4 to 3.6 use the whole dataset for the Toronto city, Tables 3.7 to 3.9 consider the summer months (May to August). Comparing the results of Table 3.4 with 3.7, we see that the coefficient of nuclear and wind power are both negative and statistically significant at 1% level across all columns. However, in Table 3.7 the magnitude of the coefficient of nuclear (wind) is higher (lower) than the results in Table 3.4. In addition, whenever significant, the coefficient of hydro and gas are still positive. However, the effect of gas declined slightly in summer (from 0.23 in column (2)-Table 3.4 to 0.14 in column (2)-Table 3.7.)

The sign of the coefficient estimates of fuel mix with respect to O_3 in Table 3.8 are the same as what the result shows in Table 3.5 except for gas and hydro. In general, gas does not show a consistent pattern and hydro shows to have a positive effect on O_3 in summer. We can use the coefficient estimates along with the summary statistics for summer to calculate the marginal effects of these fuel changes in summer. The results in Table 3.8 suggest that on average, a one percentage point increase in the proportion of hydro and wind power is associated with 0.84 *ppb* and 1.14 *ppb* increase in O_3 levels. Given that over the summer months the percentage change in hydro and wind power are -4 and 3.29, respectively; plus the fact that the mean of O_3 over the summer in Toronto is 31.45 ppb [19], these work out to a 10.64% decline and a 11.92% increase in O_3, controlling for all else. On the other hand, a one percentage point increase in the nuclear power is associated with a 0.20 *ppb* decrease in O_3 in summer. Therefore, a 4.45 percentage point

[19] Based on the authors' calculations, in summer of 2009 (2016) the proportion of nuclear, wind and hydro power are 55.46 (59.91), 1.20 (4.49) and 27.91 (23.91), respectively. On the other hand, the mean of NO_x, O_3 and $PM_{2.5}$ are 14.005 *ppb*, 31.45 *ppb* and 8.02 mg/m^3 in Toronto, respectively.

rise in nuclear power corresponds to a 0.89 O_3 reduction. Based on a O_3 sample mean of 31.45 *ppb*, this is equivalent to a 2.82% further decline in O_3. Hence, the overall marginal effect of fuel mix on O_3 is an almost 1.5% O_3 reduction during summer in Toronto.

Table 3.9 summarizes the regression results of the effects of changes in fuel mix with respect to $PM_{2.5}$ in summer. The sign of the coefficient estimates are consistent with the results shown in Table 3.6. Furthermore, with the exception of hydro, the magnitude of the coefficient of all types of fuel have increased in summer. Given the negative coefficient of wind and nuclear, and positive coefficient of hydro we can conclude that the marginal effects of fuel mix on $PM_{2.5}$ are negative. Based on a $PM_{2.5}$ sample mean of roughly 8 mg/m^3 in summer, the overall marginal effect of a 3.29 and 4.5 percentage point increase in wind and nuclear and a 4 percentage point decrease in hydro is equivalent to a significant 23.5% decline in $PM_{2.5}$.

Tables 3.10 to 3.15 contain regression results of the effects of changes in proportion of fuel mix with respect to each pollutant in Hamilton. Estimates in Table 3.10 to 3.12 are based on the whole dataset and Tables 3.13 to 3.15 focus on the summer months (May to August). With respect to NO_x, coefficient estimates of all sources of energy except wind are positive. However, the magnitude of the wind coefficient is large enough to cancel out the positive effect of nuclear on pollution. In particular, the coefficient estimate of wind in column (4) is -0.71 which implies that a one percentage point increase in wind power relative to coal is associated with 0.71 ppb decrease in NO_x in Hamilton. Therefore a 4.5 percentage point rise in the proportion of wind power is linked with a 3.19 *ppb* drop in NO_x, controlling for all else. With the NO_x sample mean of 11.13 *ppb*, this is equivalent to a 28.70% decline in NO_x. The positive effect of nuclear (ranging form 0.02 to 0.08) on NO_x is not as large as wind (ranging from -0.71 to -0.41). We calculated that the marginal effect of nuclear on NO_x to be almost 2.5%.

Table 3.11 summarizes the regression results of the effect of each type of fuel mix on O_3. There are major differences both in terms of sign and magnitude of the coefficient when we compare the results of Table 3.10 with Table 3.11. In particular, the coefficient estimates of nuclear power in Table 3.10 is positive and ranging from 0.02 to 0.08, while in Table 3.11 it is negative and ranging (in absolute value) from 0.15 to 0.37. Therefore, not only the sign of nuclear coefficient has changed, but also its magnitude. A similar trend can be seen in the coefficient of wind. In Table 3.10, the coefficient of wind is negative and larger in absolute value, however in Table 3.11, it is positively correlated with O_3 and ranging from 0.21 to 0.49. Therefore, in contrast to NO_x, an increase in nuclear and wind power have a negative effect on O_3. A 4.5 percentage point increase in wind is associated with 2.20 $(4.5*0.49)$ *ppb* increase in O_3. Given that the sample mean for O_3 is 29.37 *ppb* in Hamilton, this is equivalent to 7.49% increase in O_3. On the other hand, the negative effect of nuclear on O_3 is lower in magnitude and the marginal effect of a 5.6 percentage point increase in nuclear (which is linked to $0.89 = 5.6*0.16$ *ppb* decrease in O_3) is equivalent to an almost 3% decrease in O_3. The larger positive marginal effect of wind (7.49%) cancels out the smaller negative marginal effect of nuclear (3%). Therefore, the overall marginal effect of fuel mix on O_3 is positive, controlling for all else.

Coefficient estimates of fuel mix are also statistically significant with respect to $PM_{2.5}$, in Table 3.12. Although the sign of coefficients do not follow a consistent pattern across all columns, whenever significant, they are mostly negative (except other sources). In particular, when we control for different time fixed effects, the coefficients of all fuel types except "other", becomes negative. Since the coefficient of both nuclear and wind are negative and statistically significant (column (4)), we conclude that the overall effect of increase in these two types of power generations on declining $PM_{2.5}$ is positive. The results show that a one percentage point increase in wind (nuclear) is associated with 0.25 (0.07) mg/m^3 decrease in $PM_{2.5}$. Therefore, a 4.5 (5.6) percentage point increase in the proportion of wind (nuclear) during the sample period, is correlated with a 1.12 (0.4) mg/m^3 decrease in $PM_{2.5}$. Given the sample mean of $PM_{2.5}$ is 7.52 mg/m^3, this works out to a 14.98% (5.21%) decline in $PM_{2.5}$ level.

The reported coefficients in Table 3.13 to 3.15 summarize the regression results when we narrow down the analysis to the summer months (May to August) in Hamilton. In Table 3.13, the sign of the coefficients mostly follow the same pattern as in Table 3.10, with the exception of nuclear, which turns its sign from positive to negative as we control for time fixed effects (Column (3) to (4)). In addition, as we compare the results of these two tables, we find that the magnitude of wind and hydro are lower in summer and ranging from -0.58

to -0.31 and from 0.07 to 0.27 (whenever statistically significant), respectively. However, the magnitude of nuclear is slightly higher in absolute value (from 0.02 to 0.09). This results reinforce the negative impact of an increase in nuclear and wind power generations on NO_x in Hamilton.

In Table 3.14, the coefficient of gas is mostly insignificant; however, the coefficient of all other types of fuel are statistically significant at different levels. In addition,with the exception of hydro, all other coefficients show a consistent pattern as in Table 3.11 in terms of sign. The magnitude of hydro, nuclear and wind coefficients are increased in summer and in contrast, the magnitude of coefficient of other type is decreased in absolute value. The coefficient estimates in Table 3.11 and summary statistics help us to evaluate the overall marginal effect of an increase in nuclear and wind on O_3 levels over the sample period. The results from Table 3.11 and Table 3.3 show that the overall effect of 4.5 and 5.6 percentage point increase in wind and nuclear power on O_3 is positive during $2009-2016$. Calculating the summary statistics for summer of $2009-2016$, however, shows that although the proportion of nuclear and wind have increased by 4.45 and 3.29, respectively, the proportion of hydro power decreased from 23.91 to 27.91. This is a 4 percentage point drop in hydro and makes the overall effect of the change in fuel mix on O_3 to be negative and slightly less than 1% (0.71%) [20].

Table 3.15 contains the results of the effects of changes in fuel mix on $PM_{2.5}$ in Hamilton over the summer of $2009-2016$. The coefficient estimates are consistent in terms of sign and magnitude with the results in Table 3.12; the only exceptions are hydro that is not statistically significant across columns (2) to (4) and the coefficient of other type of energy which is significant in summer.

Table 3.16 to 3.21 contain regression results of the effects of changes in proportion of fuel mix with respect to each pollutant in Ottawa. Estimates in Table 3.16 to 3.18 are based on the whole dataset and Tables 3.19 to 3.21 focus on the summer months (May to August). With respect to NO_x, coefficient estimates of all sources of energy (whenever significant) except wind are positive. However, the magnitude of the wind coefficient is

[20]Based on authors' calculations, during the summer of $2009-2016$ in Hamilton, the mean of NO_x, O_3 and $PM_{2.5}$ are 8.96 *ppb*, 34.63 *ppb* and 8.86 mg/m^3, respectively.

large enough to cancel out the positive effect of nuclear on pollution (Column (1)). Table 3.17 summarizes the regression results of the effect of each type of fuel mix on O_3. There are major differences both in terms of sign and magnitude of the coefficient when we compare the result of Table 3.16 with Table 3.17. In particular, the coefficient estimates of nuclear power in Table 3.16 are positive and generally not statistically significant, while in Table 3.17 are negative and ranging (in absolute value) from 0.04 to 0.28. Therefore, not only the sign of nuclear coefficient has changed, but also its magnitude. A similar trend can be seen in the coefficient of wind. In Table 3.16, the coefficient of wind is negative and smaller in absolute value, however in Table 3.17, it is positively correlated with O_3 and ranging from 0.24 to 0.46. Therefore, a 4.5 percentage point increase in wind is associated with 2.07 ($4.5 * 0.0.46$) *ppb* increase in O_3. Given that the sample mean for O_3 is 26.14 *ppb* in Ottawa, this is equivalent to a 7.91% increase in O_3. On the other hand, the negative effect of nuclear on O_3 is lower in magnitude and the marginal effect of a 5.6 percentage point increase in nuclear (which is linked to $0.56 = 5.6 * 0.10$ *ppb* decrease in O_3) is equivalent to an almost 2.14% decrease in O_3. The larger positive marginal effect of wind (7.91%) cancels out the lower negative marginal effect of nuclear (2.14%). Therefore, the overall marginal effect of fuel mix on O_3 is positive, controlling for all else.

Coefficient estimates of fuel mix are also statistically significant with respect to $PM_{2.5}$, in Table 3.18. Although the sign of coefficients do not follow a consistent pattern across all columns, whenever significant, they are mostly positive (except other sources and hydro). In particular, when we control for different time fixed effects, the coefficients of all fuel types except hydro, becomes positive. Since the coefficient of both nuclear and wind are positive and statistically significant (column (4)), we conclude that the overall effect of increase in these two types of power generations on increasing $PM_{2.5}$ is positive. The results show that a one percentage point increase in wind (nuclear) is associated with 0.09 (0.02) mg/m^3 increase in $PM_{2.5}$. Therefore, a 4.5 (5.6) percentage point increase in the proportion of wind (nuclear) during the sample period, is correlated with 0.40 (0.11) mg/m^3 increase in $PM_{2.5}$. Given the sample mean of $PM_{2.5}$ is 5.53 mg/m^3, this works out to a 7.32% (2.02%) increase in $PM_{2.5}$ level.

The reported coefficients in Table 3.19 to 3.21 summarize the regression results when we narrow down the analysis to the summer months (May to August) in Ottawa. In Table 3.19, the sign of the coefficients mostly follow the same pattern as in Table 3.16, with the exception of hydro, which becomes negative and slightly more significant as we control for time fixed effects (Column (4)). In addition, as we compare the results of these two tables, we find that the magnitude of gas, hydro and wind are lower in summer; However, the magnitude of nuclear is slightly higher in absolute value (from 0.02 to 0.08). This results reinforce the negative impact of an increase in nuclear and wind power generations on NO_x in Ottawa.

In Table 3.20, the coefficient of gas is mostly insignificant; however, the coefficient of all other types of fuel are statistically significant at different levels. In addition, with the exception of hydro and total, all other coefficients show a consistent pattern as in Table 3.17 in terms of sign. The magnitude of hydro, nuclear and wind coefficients are increased in summer and in contrast, the magnitude of coefficient of other type is decreased in absolute value. The coefficient estimates in Table 3.20 and summary statistics help us to evaluate the overall marginal effect of an increase in nuclear and wind on O_3 levels over the sample period. Calculating the summary statistics for summer of $2009-2016$, shows that although the proportion of nuclear and wind have increased by 4.45 and 3.29, respectively, the proportion of hydro power decreased from 23.91 to 27.91. This is a 4 percentage point drop in hydro and makes the overall effect of the change in fuel mix on O_3 to be negative and slightly more than 1% (1.17%) [21].

Table 3.21 contains the results of the effects of changes in fuel mix on $PM_{2.5}$ in Ottawa over the summer of $2009-2016$. The coefficient estimates are consistent in terms of sign and magnitude with the results in Table 3.18. The only exceptions are gas and nuclear that are negative statistically significant across all columns in summer. Based in the summary statistics of fuel mix in summer, the overall effect of the change in fuel mix on $PM_{2.5}$ is negative and more than 6% (6.8%)

The effect of fuel mix on NO_x in Sarnia over the period of $2009-2016$ is shown in Table 3.22. Whenever statistically significant, the coefficient estimates of gas and hydro

[21] Based on authors' calculations, during the summer of $2009-2016$ in Ottawa, the mean of NO_x, O_3 and $PM_{2.5}$ are 4.44 *ppb*, 28.16 *ppb* and 5.71 mg/m^3, respectively.

are positive. On the other hand, the coefficient for nuclear energy changes its sign from positive (column (1))to negative (column (3) and (4)) as we control for more time fixed effects. Coefficients of other fuel sources do not show a consistent pattern. However, the coefficient of wind is both large in magnitude (relative to other fuel coefficients) and negative across all columns. We focus on the results in column (4), in which we include all time dummy variables, to find the marginal effect of a 5.6% increase in nuclear and 4.5% increase in wind over the sample period on NO_x in Sarnia. Coefficient estimates imply that a one percentage point increase in nuclear power relative to coal is associated with a roughly 0.02 *ppb* decline in NO_x. Therefore, a 5.6 percentage point rise in the proportion of nuclear power is linked with a 0.11 drop in NO_x, controlling for all else. With a NO_x sample mean of 10.77 *ppb*, this is equivalent to a 1.03% decline in NO_x. In addition, the marginal effects of an increase in wind power are much larger. On average, a one percentage point increase in wind power generation is associated with 0.40 *ppb* reduction in NO_x. This is a substantial 16.71% reduction in NO_x level given its sample mean of 10.77 *ppb*.

Coefficient estimates of fuel mix are statistically significant with respect to O_3, in Table 3.23. However, there are differences in signs as well as the magnitude of coefficient estimates. Coefficient estimates of nuclear power are negative and statistically significant at the 1% level, ranging from -0.52 to -0.13. Coefficient estimates of gas are also negative and statistically significant at the 1% level across all columns, with values from -0.32 to -0.05. Other fuel sources is also statistically significant but with positive coefficients. An increase in the proportion of hydro power is also significantly associated (at varying levels of significance) with lower levels of O_3. On the other hand, a rise in the proportion of wind generated power is correlated (at either 5% or 10%) with higher levels of O_3 (column (3) and (4) and (5)), ranging from 0.09 to 0.25. In contrast to NO_x, an increase in nuclear powered energy at the expense of coal is associated with larger marginal impacts with respect to reduction in O_3. A one percentage point rise in nuclear power is significantly associated with a 0.25 *ppb* reduction in O_3 levels. Hence, a 5.6 percentage point increase in nuclear power is correlated with a 1.4 *ppb* reduction in O_3 levels. Given that the sample mean of O_3 is 28.86 *ppb*, this works out to a 4.85% decline in O_3 level. On the other hand, the corresponding marginal impact for wind power are a bit lower and works in an opposite way. A one percentage point rise in hydro power generation is associated with a 0.18 *ppb* increase in O_3, which is equivalent to a 2.80% increase in O_3 level. However, taken together, the overall marginal impact of a 4.5 and 5.6 percentage point increase in wind and nuclear power on O_3 pollution is negative (2.05%) and smaller than what we find with respect to NO_x.

Table 3.24 contains estimate with respect to $PM_{2.5}$ in Sarnia. An increase in the proportion of all sources of electricity relative to coal is associated with a decline in $PM_{2.5}$ levels in Sarnia. Coefficient estimates of nuclear and wind energy are negative and significant at 1% level across all columns with coefficient estimates from -0.34 to -0.10 mg/m^3 and -0.02 to -0.12 mg/m^3, respectively. A one percentage point increase in the proportion of gas power is associated 0.07 mg/m^3 decline in $PM_{2.5}$ (column (4)). A one percentage level rise in hydro power generation is associated (at the 1% level) with a roughly 0.2 mg/m^3 decline in $PM_{2.5}$ (column (4)). Therefore, the effects of changes in fuel mix from $2009 - 2016$ on $PM_{2.5}$ in Sarnia have also been pronounced. A one percentage point rise in nuclear power is associated with a -0.12 mg/m^3 drop in $PM_{2.5}$ (column (4)). Therefore, a 5.6 percentage point rise in nuclear power generated corresponds to a 0.67 mg/m^3 reduction. Based on $PM_{2.5}$ sample mean of 9.31 mg/m^3, this is equivalent to an almost 7.20% decline in hourly $PM_{2.5}$ levels. The coefficient estimates of wind is larger at -0.25 (column (4)). The 4.5 percentage point increase in wind power over the sample period in then equivalent to a 1.12 mg/m^3 reduction in $PM_{2.5}$, which is equivalent to an almost 12% decline in $PM_{2.5}$ levels.

Table 3.25 to 3.27 contain regression result of the effects of changes in the proportion of fuel mix with respect to each pollutant in summer months (May-August) of $2009 - 2016$ in Sarnia. The estimates in Table 3.25 offer a rather contrary picture relative to estimates in Table 3.22. Estimates in column (2) to (4) in Table 3.25 indicate that a one percentage point increase in all sources of energy (relative to coal) are associated with a decrease in NO_X pollution in summer over the sample period. On the other hand, the electricity generated by hydro power generation decreased a 4 percentage point over the sample period in summer. Given the sample mean of NO_X in Sarnia is 9.03 in summer over the sample period, this works out to a 3.54% increase in NO_X level. However, the coefficient estimates of wind and nuclear are larger in absolute value at 0.30 and 0.16. The 4.45 and 3.29 percentage point increase in nuclear and wind over the sample period is then equivalent to a 0.71 and 0.98 *ppb* reduction in NO_X, which corresponds to an almost 8% and 11% decline in NO_X levels, respectively. Therefore, the overall marginal effect of changes in fuel mix in summer in Sarnia is a decline in NO_X levels.

The sign and magnitude of the coefficient estimates of fuel mix with respect to ozone in Table 3.26 are the same as the coefficient estimates in Table 3.23 except for wind and hydro. Coefficient estimates of hydro power are not only positive whenever significant (column (2) to (4)), but also larger in magnitude, ranging from 0.33 to 0.51. On the other hand, the coefficient estimates of wind are positive, larger in magnitude and significant at 1% level across all columns. Given that the sample mean of ozone is roughly 33.5 *ppb*, a 4.45 and 3.29 percentage point increase in nuclear and wind and a 4 percentage point decline in hydro power generation over the sample period, works out to an overall 3.92% decline in ozone levels.

Table 3.27 contains estimates with respect to $PM_{2.5}$. Similar to Table 3.24, an increase in the proportion of all fuel mix relative to coal is associated with a decline in $PM_{2.5}$ level. In addition, with the exception of other sources, the coefficient estimate of all sources of energy are slightly larger than the coefficients in Table 3.24. Based on the $PM_{2.5}$ sample mean of 9.96 mg/m^3, the marginal effect of a 4.45 and 3.29 percentage point increase in nuclear and wind are equivalent to a 11.61% and 9.57% decline in $PM_{2.5}$ levels. On the other hand, a 4 percentage point decline in hydro power generations over the sample period, works out to a 12.44% decrease in $PM_{2.5}$ level. Therefore, the overall marginal effect of fuel mix change on $PM_{2.5}$ over the sample period is still negative.

An increase in the total electricity produced over the sample period is mostly associated (at varying levels of significance) with higher levels of pollution in all the cities; However, over the summer months, the coefficient of total does not show a consistent pattern both in terms of sign and level of statistical significance. Further, the results show that higher temperature is associated with higher O_3 and $PM_{2.5}$ levels in all cities. On the other hand, temperature is correlated with lower NO_x levels in Toronto and Hamilton, and it does not show to have a conclusive effect on NO_x pollution in Sarnia. In addition, relative humidity is positively associated with NO_x and $PM_{2.5}$, while it is negatively correlated with O_3 levels in all four cities.

In all four cities, wind has a negative effect on NO_x and a positive effect on O_3 pollution. This is mainly due to the intermittent nature of wind power generators. In Ontario, the production of electricity by wind power plants is supported by the natural gas power generators. Therefore, while wind is dispersing the NO_x, the production of the electricity by gas power plants generates NO_x pollution, which in turn contributes to the formation of O_3. Therefore, wind decreases the level of NO_x and increases the level of O_3 in all cases.

To enhance the credibility of the empirical results, we run a sensitivity analysis. Tables 3.28, 3.29, 3.30 and 3.31 show the results from GLS analysis in which the cluster-standard errors at the day level and Newey-West standard errors are considered. Based on the Newey-West standard error, the structure of the error term is considered to be heteroskedastic and autocorrelated up to lag 6[22] We specifically focus on the fully-specified GLS model in all regressions. Reg (1) in Tables 3.28, 3.29, 3.30 and 3.31 shows the results of the regressions when the standard errors are clustered at the day level over the period from January 2009 to December 2016[23]. Reg (2) considers the Newey-West standard error structure.

Overall, Reg (2) in which we consider Newey-West standard error structure, shows the same or higher significance level for all of the coefficient estimates, with the exception of nuclear power in NO_x and temperature in O_3 regressions in Sarnia. On the other hand, coefficient estimates in Reg (1) for all fuel types in the four cities, shows the same or a lower significance level. Although some of the coefficients in Reg (1) are at a lower significant level, the statistical significance level of the two important coefficients of nuclear and wind have not changed much. The only exceptions are the nuclear coefficient in $PM_{2.5}$ analysis in Toronto and NOx analysis in Hamilton and Sarnia that are not significant anymore; However, the coefficient of wind in all three situations is still negative and statistically

[22]We allow for the possibility of autocorrelation in the error terms up to lag 6 in each regression since lag 3 and lag 6 of the dependent variable is considered in the time-series analysis. In addition, we considered the Newey-West error terms to be autocorrelated up to lag 1 to 6 and the results did not change significantly.

[23]This period excludes the data from September 2014 to December 2014 since the fuel mix data for these four months are not available.

significant at the 1% level. This shows that the the change in fuel mix can still be associated to a decline in $PM_{2.5}$ level in Toronto and NOx level in Hamilton and Sarnia (through a rise in wind power).

3.5.2 The effects of changing fuel mix on smog days

Tables 3.32 and 3.33 contain the results of probit analysis detailing the effects of changes in fuel mix on the likelihood of smog days, with the dependent variable being 1 in the event of a smog day and 0 otherwise. In both tables, column (1) contains estimates without the addition of any dummy, economic or weather variables. In column (2) we add the total electricity produced and weather to the set of independent variables. Column (3) contains estimates conditioned on month and year dummies. Column (4) evaluates the sensitivity of findings through the addition of monthly exchange and unemployment rates, total electricity produced and year dummies. Unlike the previous tables, the results in these tables are based on daily averages. Table 3.32 is based on the dataset that contains fuel mix from March to October of 2009-2014 (8 months in each year). During these months 58 smog days are reported. In Table 3.33, we focus on summer months (June-August) in which 38 smog days are reported. In both tables we reported the marginal effects of independent variables.

In Table 3.32, results show that the marginal effects of gas power are not statistically significant across columns. The marginal effect of hydro power is statistically significant at the 1% level in column (1), and becomes both positive and reduced in statistical precision in column (3), specifically to the 10% level. On the other hand, the marginal effect of wind, although small, is negative across all columns. The marginal effect of nuclear is positive, very small in magnitude and statistically significant is column (3).

In contrast to Table 3.32, in Table 3.33 when we focus on summer months, the marginal effect of gas becomes negative across columns, however it is not statistically significant. The marginal effect of hydro power is negative and statistically significant at the 1% level in column (1). This suggests that on average, higher electricity generation by hydro power are correlated with lower incidence of smog day. However, the marginal effect of hydro is not statistically significant across all other columns and changes its sign from negative to positive in column (3) and (4). The marginal effect of wind power is still negative across columns and statistically significant at 10% level in column (1) and (2). Similar to Table 3.32, the coefficient of nuclear power is positive whenever significant; Furthermore, in contrast to Table 3.32 adding the time dummy variables does not increase its statistical precision. The marginal effect of the daily average temperature are statistically significant at 1% level in column (2) only, and suggests that on average, higher temperatures are correlated with a higher incidence of smog days.

3.6 Summary of Findings and Policy Implications

Relying on coal-fired energy is not conducive to a cleaner air quality. This is a fact that has been established by numerous scientific papers. Ontario is the first North American jurisdiction to completely eliminate coal-fired electricity generation, and is therefore offers unique identifying variation in order to evaluate corresponding environmental benefits. The study employs data across four Ontario cities from 2009-2016, a time period, which contains observations for years after which coal had been eliminated (in 2014).

The empirical estimates offer support to the notion that cleaner sources of energy are significantly associated with cleaner air quality. There are instances where coefficient estimates of gas and hydro powered generation possess positive coefficients (with respect to higher levels of pollutants) and more wind energy is correlated with increased levels of O_3. However, the vast majority of results do suggest that more nuclear and wind energy, at the expense of coal, is correlated with decreased levels of NO_x and $PM_{2.5}$. An increase in nuclear powered generation is associated with reduced O_3 levels. On the other hand, the results do not suggest a statistically significant correlation between different types of fuel mix and the elimination of smog days.

This study has not addressed from a cost-benefit perspective, whether the benefits from these improvements in air quality outweigh the costs incurred by the government in subsidies given to renewable sources of energy as well as guaranteed rate contracts to nuclear and gas plants. Possible next steps involve quantifying the health benefits from these reductions in pollutants and the costs which associated with eliminating coal and this will be challenging. The question that needs to be answered is how many fewer premature deaths have been avoided because of the reduction in pollution as well as reductions in morbidity. A report by the Ontario Public Health Association (2002) was particularly influential in motivating policymakers to eliminate coal, and might be useful [24]. Such health benefits need to be compared against the Global Adjustment payments that electricity consumers in Ontario are charged to finance long term guaranteed payments to generators that produce renewable sources of energy. This is a non-trivial undertaking and will be addressed in future research.

[24] Available at, https://cape.ca/wpcontent/uploads/2015/10/Beyond_Coal_-_Power_Public_Health_and_the_Environment.pdf

3.7 Tables

Table 3.1: Phasing out coal-fired generators

Plant (Capacity (MW))	2003	2005	2010	2011	2012	2013	2014
Lakeview	1150						
Nanticoke	3940	3940	2960	1980	1980		
Lambton	1980	1980	1010	1010	1010		
Thunder Bay	306	306	306	306	306	306	(April)
Atikokan	211	211	211	211			
Total	7587	6437	4487	3507	3296	306	0

Source: Ontario Ministry of Energy.

Table 3.2: Summary Statistics

	2009		**2010**		**2011**		**2012**		**2013**		**2014**		**2015**		**2016**	
	(%)	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**	**(%)**	**(MW/hour)**
Coal	6.16	1123.60	7.82	1435.09	2.48	466.86	2.66	490.36	1.82	354.75	0.89	16.23	0	0	0	0
	(5.08)	(1012.02)	(5.93)	(1201.94)	(2.98)	(622.86)	(2.32)	(475.02)	(2.12)	(441.46)	(0.17)	(33.18)	(0)	(0)	(0)	(0)
Gas	10.18	1763.89	13.16	2341.38	14.08	2510.95	14.38	2545.97	10.7	1978.86	9.96	1827.76	9.95	1788.03	8.34	1481.14
	(3.76)	(794.97)	(5.17)	(1175.53)	(5.46)	(1227.48)	(5.71)	(1269.84)	(5.53)	(1227.07)	(5.73)	(1258.68)	(6.04)	(1228.23)	(5.34)	(1105.92)
Hydro	25.21	4255.44	20.3	3505.69	22.15	3801.08	21.51	3693.55	23.1	4019.18	23.77	4131.18	23.38	4065.10	23.44	3982.66
	(5.08)	(953.02)	(4.51)	(983.18)	(4.31)	(911.18)	(4.21)	(881.71)	(3.58)	(777.66)	(3.66)	(723.56)	(3.60)	9801.65)	(4.15)	(821.66)
Nuclear	55.98	9360.79	55.97	9458.59	57.84	9741.37	57.31	9693.95	60	10347.62	61.23	10561.68	60.55	10480.03	61.60	10395.71
	(8.98)	(1354.38)	(8.32)	(984)	(7.43)	(753.68)	(7.52)	(797.92)	(6.86)	(783.98)	(6.21)	(802.63)	(6.96)	(1436.9)	(6.39)	(994.16)
Other	0.9	150.53	0.83	144.61	0.8	136.44	1	173.19	0.89	155.28	0.88	153.37	0.33	58.66	0.50	87.28
	(0.44)	(78.16)	(0.41)	(95.91)	(0.27)	(56.76)	(0.34)	(76.33)	(0.22)	(47.7)	(0.53)	(106.06)	(0.32)	(57.76)	(0.510	(88.24)
Wind	1.55	259.92	1.89	318.43	2.63	441.36	3.1	526.53	3.4	592.73	4.05	712.65	5.76	996.02	6.10	1053.53
	(1.27)	(209.23)	(1.51)	(254.05)	(2.22)	(362.17)	(2.39)	(404)	(2.47)	(436.42)	(3.12)	(558.47)	(4.24)	(734.36)	(4.33)	(789.66)
Total		16914.2		17203.81		17098.09		17123.58		17448.45		17402.9		17387.87		17000.34
		(2466.31)		(2645.82)		(2304.25)		(2223.75)		(2118.95)		(1948.96)		(2273.9)		(2000.56)
Observations		8760		8760		8760		8784		8760		5832		8760		8784
Exchange		114.1535		103.01		98.92		99.93		103.01		109.35		127.89		132.55
		(7.9)		(1.63)		(2.44)		(1.40)		(1.88)		(1.18)		(4.88)		(3.89)
Unemployment		9.10		8.68		7.9		7.92		7.58		7.38		6.74		6.55
		(0.41)		(0.36)		(0.2)		(0.2)		(0.16)		(0.11)		(0.13)		(0.20)
Observations		12		12		12		12		12		8		12		12

Source: Authors' own calculation.

Note: Standard errors are in parentheses.

Table 3.3: Summary Statistics of the mean of different type of pollutants and weather condition

	2009	2010	2011	2012	2013	2014	2015	2016	2009-2016
Toronto:									
NO_x (ppb)	21.648	20.34	18.51	16.31	16.06	16.29	16.045	15.92	17.71
	(15.25)	(16.11)	(13.91)	(12.49)	(11.99)	(13.24)	(12.13)	(12.09)	(13.66)
O_3 (ppb)	24.64	26.02	25.4	26.55	26.3	28.63	25.67	25.52	25.97
	(13.01)	(13.93)	(13.21)	(14.71)	(12.57)	(11.90)	(13.12)	(12.01)	(13.17)
$PM_{2.5}$ (mg/m^3)	5.54	6.01	6.24	6.42	8.25	9.13	8.36	6.96	7.02
	(5.13)	(6.12)	(5.57)	(5.80)	(6.47)	(6.89)	(6.24)	(4.70)	(5.97)
Temperature ($°C$)	9.11	10.34	10.13	11.29	9.56	8.20	9.39	10.71	9.91
	-9.99	(10.41)	(10.60)	(9.69)	(10.41)	(12.34)	(11.24)	(10.63)	(10.64)
Rel. Humidity (%)	72.35	71.88	74.97	73.27	68.64	64.95	67.02	64.61	69.93
	-16.98	(16.48)	(15.67)	(16.21)	(16.01)	(15.96)	(15.81)	(17.15)	(16.70)
Observation	8696	8613	8566	8566	8497	5605	8699	8585	65827
Hamilton:									
NO_x (ppb)	12.41	11.21	12.21	10.59	11.05	11.77	10.88	9.15	11.13
	(12.50)	(12.74)	(11.8)	(11.07)	(12.40)	(11.33)	(10.30)	(9.28)	(11.53)
O_3 (ppb)	27.10	29.65	28.82	30.13	29.41	31.88	29.41	29.41	29.37
	(13.57)	(13.93)	(13.82)	(15.28)	(12.64)	(12.41)	(13.23)	(12.27)	(13.52)
$PM_{2.5}$ (mg/m^3)	6.34	6.19	6.65	6.52	9.23	9.89	9.046	7.20	7.52
	(5.39)	(6.55)	(6.27)	(6.21)	(7.54)	(7.23)	(7.04)	(5.39)	(6.60)
Temperature ($°C$)	8.37	9.49	9.13	10.54	8.07	7.53	8.70	10.12	9.06
	(10.16)	(10.59)	(10.85)	(9.91)	(10.38)	(12.66)	(11.55)	(10.80)	(10.85)
Rel. Humidity (%)	73.11	71.05	73.09	74.29	74.33	70.99	70.92	70.07	72.27
	(18.38)	(17.36)	(17.03)	(18.68)	(15.87)	(16.93)	(17.26)	(18.47)	(17.62)
Observation	8504	8673	8635	8559	8260	5755	8552	8633	65571
Ottawa:									
NO_x (ppb)	8.2326	7.5523	8.1555	8.6888	9.4505	7.6233	7.5467	7.2533	8.0852
	(12.9730)	(10.6207)	(11.4129)	(13.1307)	(13.5236)	(9.7599)	(11.4265)	(9.2693)	(11.7152)
O_3 (ppb)	24.6322	26.5670	24.8577	25.6062	26.5918	29.2084	26.9629	25.7880	26.1439
	(12.6641)	(12.4750)	(11.8660)	(12.9815)	(12.0229)	(11.7024)	(12.2711)	(11.6847)	(12.3034)
$PM_{2.5}$ (mg/m^3)	4.3699	4.3110	4.4862	5.0190	7.0886	6.9698	6.8752	5.6414	5.5308
	(4.3544)	(5.3969)	(4.1523)	(4.6109)	(6.1247)	(5.2893)	(4.9515)	(4.6552)	(5.0937)
Temperature ($°C$)	6.5521	8.1949	7.3307	8.1401	6.5349	6.4192	6.9755	7.6809	7.2674
	(11.7232)	(11.2017)	(12.0457)	(11.9284)	(12.5068)	(14.1799)	(13.2521)	(12.4524)	(12.3705)
Rel. Humidity (%)	73.8603	72.0302	72.7506	71.2845	73.3489	69.1989	70.1657	69.3791	71.6135
	(18.6322)	(18.9589)	(18.4725)	(19.4934)	(17.2962)	(17.2513)	(17.6723)	(19.2100)	(18.5140)
Observation	8568	8677	8401	8616	8583	5507	8545	8418	65315
Sarnia:									
NO_x (ppb)	10.92	10.19	11.68	10.72	9.79	10.63	11.62	10.64	10.77
	(10.21)	(11.65)	(10.82)	(9.55)	(9.07)	(11.43)	(10.47)	(11.51)	(10.61)
O_3 (ppb)	26.55	30.66	29.57	29.7	28.48	29.97	27.74	28.49	28.86
	(12.54)	(13.53)	(13.41)	(15.05)	(12.51)	(12.52)	(11.94)	(12.05)	(13.07)
$PM_{2.5}$ (mg/m^3)	9.76	10.42	10.44	10.21	8.42	9.32	8.51	7.29	9.31
	(6.41)	(7.68)	(6.77)	(6.27)	(5.92)	(7.35)	(6.83)	(5.25)	(6.66)
Temperature ($°C$)	9.13	9.17	9.35	9.32	9.36	9.05	9.71	9.18	9.29
	(10.85)	(10.82)	(11)	(11.11)	(11.04)	(11.19)	(10.87)	(10.77)	(10.95)
Rel. Humidity (%)	74.06	73.37	72.94	73.71	73.30	71.62	72.19	72.99	73.09
	(15.35)	(16.24)	(16.68)	(16.16)	(15.69)	(15.64)	(16.23)	(15.21)	(15.93)
Observation	8573	8699	8642	8505	8380	5693	7930	8564	64981

Source: Authors' own calculation.

Note: Standard errors are in parentheses.

Table 3.4: GLS & Time-Series Estimates of Fuel Mix on NO_x (Toronto)

Dependent Var: NO_x **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.0535	0.2306***	0.2155***	0.1384***	0.0767***
	(0.0380)	(0.0418)	(0.0418)	(0.0410)	(0.0184)
Hydro	0.1242***	0.1641***	0.1006***	0.008	0.1142***
	(0.039)	(0.0303)	(0.0396)	(0.038)	(0.0174)
Nuclear	-0.1357***	0.0012	-0.0077	-0.0103	-0.0283*
	(0.0139)	(0.0248)	(0.0255)	(0.021)	(0.0155)
Other	0.097	1.3353***	1.094***	0.2552	-0.0022
	(0.121)	(0.1975)	(0.1857)	(0.1797)	(0.1087)
Wind	-0.8482***	-0.7743***	-0.9278***	-0.9733***	-0.5381***
	(0.0673)	(0.0624)	(0.0731)	(0.0723)	(0.0104)
Total	0.0005***	0.0005***	0.0005***	0.0001	0.0001***
	(0.0001)	(0.00009)	(0.00009)	(0.00008)	(0.00002)
Lag3-NO_x	NA	NA	NA	NA	0.4755***
					(0.0104)
Lag6-NO_x	NA	NA	NA	NA	0.0453***
					(0.0059)
Temperature	-0.2897***	-0.3088***	-0.0863***	-0.1176***	-0.1768***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.0062)
Relative Humidity	0.0754***	0.0957***	0.079***	0.0845***	0.1275***
	(0.0131)	(0.0132)	(0.0131)	(0.0031)	(0.0026)
Constant	12.2039***	2.4712***	5.7538***	18.7167***	0.1913
	(3.0213)	(1.1946)	(1.7061)	(2.2553)	(1.6772)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66614	66614	66614	66614	66054
R^2	0.1252	0.1477	0.1493	0.2218	0.4027

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.5: GLS & Time-Series Estimates of Fuel Mix on O_3 (Toronto)

Dependent Var: O_3 **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	-0.2868***	-0.346***	-0.1449***	-0.062***	-0.0394***
	(0.0251)	(0.0178)	(0.017)	(0.0266)	(0.0127)
Hydro	-0.0892***	-0.0419	-0.1934***	-0.1324***	-0.1498***
	(0.0334)	(0.0254)	(0.0269)	(0.0275)	(0.0129)
Nuclear	-0.3644***	-0.3779***	-0.1629***	-0.1628***	-0.0648***
	(0.0126)	(0.0159)	(0.015)	(0.0146)	(0.0113)
Other	1.4205***	0.3689*	0.6283***	1.5162***	1.1589***
	(0.3045)	(0.2056)	(0.2003)	(0.0984)	(0.0946)
Wind	0.3467***	0.4304***	0.6637***	0.7074***	0.2592***
	(0.0559)	(0.0805)	(0.0694)	(0.069)	(0.0146)
Total	0.0007***	0.0008***	0.0007***	0.0011***	0.0004***
	(0.00008)	(0.00009)	(0.00009)	(0.00009)	(0.00002)
Lag3-O_3	NA	NA	NA	NA	0.5871***
					(0.0047)
Lag6-O_3	NA	NA	NA	NA	-0.0321***
					(0.0045)
Temperature	0.4526***	0.4666***	0.4579***	0.4966***	0.2898***
	(0.0276)	(0.0244)	(0.0325)	(0.0267)	(0.0049)
Relative Humidity	-0.2426***	-0.2571***	-0.2097***	-0.2175***	-0.1753***
	(0.0118)	(0.0118)	(0.0119)	(0.0126)	(0.001)
Constant	50.2931***	48.7024***	30.515***	21.1209***	17.4922***
	(2.0323)	(2.2511)	(1.4847)	(2.311)	(1.213)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66885	66885	66885	66885	66385
R^2	0.3311	0.3426	0.4076	0.4682	0.6702

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.6: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Toronto)

Dependent Var: $PM_{2.5}$ **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.0895***	-0.0544***	-0.0191*	0.005	0.0135*
	(0.0095)	(0.0101)	(0.0105)	(0.0086)	(0.0060)
Hydro	0.1178***	-0.0887***	-0.1053***	-0.0486***	0.0059
	(0.0091)	(0.0104)	(0.0094)	(0.0153)	(0.0065)
Nuclear	0.147***	-0.0721***	-0.0393***	-0.0348***	-0.0045
	(0.0087)	(0.0067)	(0.0075)	(0.0066)	(0.0054)
Other	0.0619	0.2085	0.2253*	0.3716***	-0.0375
	(0.2083)	(0.1339)	(0.1319)	(0.1227)	(0.0468)
Wind	0.0927***	-0.1844***	-0.1862***	-0.1573***	-0.066***
	(0.0086)	(0.0123)	(0.0113)	(0.0103)	(0.0072)
Total	0.0007***	0.0004***	0.0004***	0.0005***	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00001)
Lag3-$PM_{2.5}$	NO	NO	NO	NO	0.5864***
					(0.0078)
Lag6-$PM_{2.5}$	NO	NO	NO	NO	0.1519***
					(0.0073)
Temperature	0.1457***	0.1385***	0.2544***	0.2717***	0.0603***
	(0.0036)	(0.0032)	(0.0037)	(0.0032)	(0.0027)
Relative Humidity	0.0636***	0.0784***	0.0803***	0.0738***	0.026***
	(0.0021)	(0.0018)	(0.0021)	(0.0015)	(0.0009)
Constant	-24.3862	-2.2545**	-4.2879***	-8.9507***	-3.8656***
	(1.2445)	(1.094)	(1.1070)	(1.1742)	(0.6)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66288	66288	66288	66288	65291
R^2	0.1142	0.1601	00.1854	0.1936	0.5814

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.7: GLS & Time-Series Estimates of Fuel Mix on NO_x (Toronto)

Dependent Var: NO_x **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	0.1774***	0.1444***	0.0473	0.0241
	(0.0247)	(0.0392)	(0.0273)	(0.0254)
Hydro	0.1857***	0.1414***	0.0002	0.0146
	(0.0394)	(0.0447)	(0.048)	(0.0263)
Nuclear	-0.0752***	-0.1006***	-0.1483***	-0.0842***
	(0.0163)	(0.0143)	(0.0228)	(0.022)
Other	0.3795	0.5907***	-0.1254	-0.4607***
	(0.1277)	(0.1599)	(0.1861)	(0.1215)
Wind	-0.638***	-0.785***	-0.7721***	-0.5678***
	(0.0657)	(0.0658)	(0.0637)	(0.0307)
Total	0.0001	0.0002**	-0.0006***	-0.0003***
	(0.0001)	(0.00009)	(0.0001)	(0.00005)
Lag3-NO_x	NA	NA	NA	0.4467***
				(0.0119)
Lag6-NO_x	NA	NA	NA	0.0453***
				(0.009)
Temperature	-0.1627***	-0.1933***	-0.0333	-0.1051***
	(0.0394)	(0.0398)	(0.0503)	(0.0175)
Relative Humidity	0.0122	0.0269**	0.0507***	0.0695***
	(0.0142)	(0.0143)	(0.0143)	(0.0039)
Constant	12.6527***	14.8698***	33.6235***	16.1152***
	(3.4949)	(3.0713)	(4.8981)	(2.6167)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23292	23292	23292	23057
R^2	0.0419	0.057	0.1827	0.3097

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.8: GLS & Time-Series Estimates of Fuel Mix on O_3 (Toronto)

Dependent Var: O_3 **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1785***	0.001	0.0806**	0.0652**
	(0.0326)	(0.039)	(0.0351)	(0.0291)
Hydro	0.1661***	0.7744***	0.8444***	0.3525***
	(0.0441)	(0.0663)	(0.0662)	(0.029)
Nuclear	-0.5157***	-0.2141***	-0.2012***	-0.079***
	(0.0197)	(0.0288)	(0.0369)	(0.0227)
Other	1.8834***	1.3958***	2.1549***	1.6283***
	(0.3011)	(0.1997)	(0.1502)	(0.1517)
Wind	0.9975***	1.4517***	1.4148***	0.6487***
	(0.1058)	(0.1042)	(0.1117)	(0.0345)
Total	-0.00009	0.0002***	0.0009***	0.0001***
	(0.00008)	(0.00007)	(0.0001)	(0.00005)
Lag3-O_3	NA	NA	NA	0.5611***
				(0.0077)
Lag6-O_3	NA	NA	NA	-0.0391***
				(0.0072)
Temperature	1.0636***	1.2609***	1.1146***	0.5948***
	(0.0246)	(0.0544)	(0.0543)	(0.0184)
Relative Humidity	-0.0983***	-0.1138***	-0.1125***	-0.1163***
	(0.0051)	(0.0073)	(0.01)	(0.0043)
Constant	41.8238***	-4.6243	-18.1635***	-0.3814
	(3.3123)	(3.9897)	(4.9629)	(2.6181)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23486	23486	23486	23296
R^2	0.3829	0.4299	0.4944	0.6558

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.9: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Toronto)

Dependent Var: $PM_{2.5}$ **(Toronto)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1564***	-0.2493***	-0.2196***	-0.0534***
	(0.0176)	(0.0105)	(0.0113)	(0.0148)
Hydro	0.0173	-0.0877***	0.0496	-0.00041
	(0.0113)	(0.0204)	(0.0315)	(0.0148)
Nuclear	-0.0917***	-0.2713***	-0.2355***	-0.0684***
	(0.0106)	(0.0158)	(0.0157)	(0.0117)
Other	0.6529***	0.4619***	0.5545***	-0.1165**
	(0.1582)	(0.1542)	(0.1454)	(0.0744)
Wind	-0.0491***	-0.2521***	-0.2174***	-0.10***
	(0.0192)	(0.0139)	(0.015)	(0.0177)
Total	0.00007**	-0.0002***	-0.000009	-0.00008***
	(0.00004)	(0.00006)	(0.00008)	(0.00002)
Lag3-$PM_{2.5}$	NA	NA	NA	0.5421***
				(0.0119)
Lag6-$PM_{2.5}$	NA	NA	NA	0.1747***
				(0.0107)
Temperature	0.56498***	0.5965***	0.6188***	0.1627***
	(0.0117)	(0.0118)	(0.0122)	(0.0095)
Relative Humidity	0.0806***	0.1054***	0.0952***	0.0291***
	(0.0055)	(0.0056)	(0.0056)	(0.0022)
Constant	-3.4971**	13.1064***	2.3971	2.7084
	(2.196)	(2.8577)	(3.3151)	(1.3673)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23318	23318	23318	22941
R^2	0.1940	0.2379	0.251	0.5645

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.10: GLS & Time-Series Estimates of Fuel Mix on NO_x (Hamilton)

Dependent Var: NO_x **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.2532***	0.2176***	0.2218***	0.1716***	0.1097***
	(0.0146)	(0.0471)	(0.0173)	(0.0371)	(0.016)
Hydro	0.3998***	0.3577***	0.2661***	0.1825***	0.2085***
	(0.0390)	(0.0467)	(0.0471)	(0.0378)	(0.0149)
Nuclear	0.0814***	0.0213*	0.0577***	0.0597***	0.0181
	(0.0118)	(0.0148)	(0.015)	(0.0147)	(0.0129)
Other	0.2994**	1.0308***	0.84***	0.2641***	-0.0202
	(0.1276)	(0.0718)	(0.066)	(0.0776)	(0.0728)
Wind	-0.5174***	-0.6321***	-0.7045***	-0.7152***	-0.4137***
	(0.0356)	(0.0401)	(0.0407)	(0.0404)	(0.0175)
Total	0.0001**	0.00006	0.0002***	-0.00005	0.0001***
	(0.00005)	(0.00006)	(0.00006)	(0.00005)	(0.00002)
Lag3-NO_x	NA	NA	NA	NA	0.4639***
					(0.0113)
Lag6-NO_x	NA	NA	NA	NA	0.0639***
					(0.0071)
Temperature	-0.2403***	-0.2473***	-0.2121***	-0.2454***	-0.1892***
	(0.001)	(0.001)	(0.003)	(0.0329)	(0.005)
Relative Humidity	0.1813***	0.188***	0.1903***	0.1954***	0.135***
	(0.007)	(0.009)	(0.009)	(0.0067)	(0.0024)
Constant	-17.5935***	-12.9075***	-14.1968***	-2.8265**	-10.4945***
	(2.6109)	(3.1465)	(3.0914)	(1.9181)	(1.4303)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66265	66265	66265	66265	65575
R^2	0.1780	0.1836	0.1895	0.22	0.4219

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.11: GLS & Time-Series Estimates of Fuel Mix on O_3 (Hamilton)

Dependent Var: O_3 **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	-0.1756***	-0.3463***	-0.1364***	-0.0571**	-0.0494***
	(0.0142)	(0.0167)	(0.0360)	(0.0255)	(0.0119)
Hydro	-0.1045**	-0.2893***	-0.3298***	-0.2326***	-0.1949***
	(0.0535)	(0.0462)	(0.0157)	(0.0461)	(0.0121)
Nuclear	-0.2277***	-0.3745***	-0.1517***	-0.1645***	-0.0601***
	(0.0115)	(0.0144)	(0.0139)	(0.0133)	(0.0106)
Other	0.9375***	-0.1417	0.1545	0.9447***	1.0079***
	(0.1055)	(0.2254)	(0.2193)	(0.1666)	(0.0759)
Wind	0.3374***	0.2146***	0.4845***	0.4964***	0.2549***
	(0.0152)	(0.0496)	(0.0491)	(0.0385)	(0.0141)
Total	0.00008	0.0006***	0.0007***	0.0011***	0.0004***
	(0.00006)	(0.00006)	(0.00008)	(0.00009)	(0.00001)
Lag3-O_3	NA	NA	NA	NA	0.5501***
					(0.005)
Lag6-O_3	NA	NA	NA	NA	-0.0056
					(0.0045)
Temperature	0.4313***	0.4337***	0.5051***	0.5174***	0.3321***
	(0.0041)	(0.0042)	(0.0219)	(0.0161)	(0.0047)
Relative Humidity	-0.3299***	-0.3347***	-0.3005***	-0.3002***	-0.2105***
	(0.0026)	(0.0026)	(0.0125)	(0.0075)	(0.0012)
Constant	50.9307***	69.3374***	42.9863***	30.9167***	23.2347***
	(4.1415)	(3.5683)	(4.2262)	(3.7588)	(1.1533)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66599	66599	66599	66599	65928
R^2	0.4171	0.4223	0.4861	0.5244	0.7173

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.12: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Hamilton)

Dependent Var: $PM_{2.5}$ **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.0388***	-0.1213***	-0.0652***	-0.0476***	-0.007
	(0.01)	(0.0098)	(0.0088)	(0.0088)	(0.0072)
Hydro	0.1722***	-0.0619***	-0.1088***	-0.0763***	0.001
	(0.0180)	(0.01)	(0.0096)	(0.0102)	(0.0077)
Nuclear	0.1077***	-0.1367***	-0.0716***	-0.0797***	-0.0218***
	(0.0097)	(0.0064)	(0.0075)	(0.0064)	(0.0065)
Other	-0.0774	0.0482	0.0558	0.2049*	0.0324
	(0.1725)	(0.1374)	(0.0667)	(0.1276)	(0.0463)
Wind	0.0076	-0.2898***	-0.2673***	-0.254***	-0.1184***
	(0.013)	(0.0114)	(0.0117)	(0.0117)	(0.0087)
Total	0.0006***	0.0003***	0.0003***	0.0004***	0.0001***
	(0.00002)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
Lag3-$PM_{2.5}$	NA	NA	NA	NA	0.5459***
					(0.0099)
Lag6-$PM_{2.5}$	NA	NA	NA	NA	0.1348***
					(0.0099)
Temperature	0.1348***	0.1245***	0.2087***	0.2182***	0.053***
	(0.0034)	(0.0034)	(0.0037)	(0.0038)	(0.0029)
Relative Humidity	0.1091***	0.1002***	0.1217***	0.1173***	0.052***
	(0.0025)	(0.0025)	(0.0015)	(0.0026)	(0.0012)
Constant	-22.5678***	3.1503***	-3.1841***	-6.1897***	-4.2463***
	(1.4293)	(1.6002)	(1.066)	(1.0972)	(0.7192)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66186	66186	66186	66186	65281
R^2	0.10	0.1421	0.1761	0.1767	0.5193

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.13: GLS & Time-Series Estimates of Fuel Mix on NO_x (Hamilton)

Dependent Var: NO_x **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	0.2465***	0.119***	0.0682**	0.0629***
	(0.0304)	(0.0349)	(0.0343)	(0.0205)
Hydro	0.2779***	0.1334***	0.0465	0.0732***
	(0.0261)	(0.0266)	(0.0388)	(0.0218)
Nuclear	0.0998***	-0.0769**	-0.0989***	-0.0281*
	(0.0221)	(0.0105)	(0.0102)	(0.0165)
Other	0.1274	0.3964***	0.0429	-0.1478
	(0.1774)	(0.1049)	(0.0965)	(0.0871)
Wind	-0.3126***	-0.5813***	-0.574***	-0.361***
	(0.0411)	(0.067)	(0.0699)	(0.0257)
Total	0.0006***	0.0003	0.00008	0.0003***
	(0.00005)	(0.00006)	(0.00009)	(0.00004)
Lag3-NO_x	NA	NA	NA	0.4461***
				(0.0175)
Lag6-NO_x	NA	NA	NA	0.0791***
				(0.0125)
Temperature	-0.602***	-0.5884***	-0.5872***	-0.3805***
	(0.0295)	(0.0266)	(0.037)	(0.0138)
Relative Humidity	0.0857***	0.0919***	0.1094***	0.0674***
	(0.0088)	(0.007)	(0.007)	(0.0034)
Constant	-9.5421***	5.900**	15.7913***	0.4812
	(1.776)	(2.8328)	(3.2014)	(2.0319)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23286	23286	23286	23035
R^2	0.1823	0.1929	0.2448	0.4214

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “coal”. Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.14: GLS & Time-Series Estimates of Fuel Mix on O_3 (Hamilton)

Dependent Var: O_3 **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1643***	-0.0673	0.006	0.002
	(0.0412)	(0.0479)	(0.0467)	(0.0247)
Hydro	0.1077*	0.5366***	0.6506***	0.3224***
	(0.0605)	(0.0883)	(0.0792)	(0.0266)
Nuclear	-0.4459***	-0.2555***	-0.2239***	-0.0991***
	(0.0188)	(0.0203)	(0.0193)	(0.0203)
Other	1.5479***	0.9424***	1.51544***	1.2248***
	(0.2057)	(0.2331)	(0.1587)	(0.1244)
Wind	0.7115***	1.0163***	1.0174***	0.546***
	(0.0669)	(0.0765)	(0.0753)	(0.0307)
Total	-0.0003***	-0.0008	0.0003**	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.00004)
Lag3-O_3	NA	NA	NA	0.5538***
				(0.0078)
Lag6-O_3	NA	NA	NA	-0.0128*
				(0.0072)
Temperature	1.2224***	1.3143***	1.2929***	0.8419***
	(0.0262)	(0.02353)	(0.024)	(0.0173)
Relative Humidity	-0.1598***	-0.1595***	-0.1897***	-0.1489***
	(0.0102)	(0.0123)	(0.0158)	(0.0037)
Constant	50.7081***	20.12**	4.5863	9.0494***
	(4.9277)	(6.7835)	(5.3805)	(2.3806)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23282	23282	23282	23013
R^2	0.4672	0.4943	0.5554	0.7244

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.15: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Hamilton)

Dependent Var: $PM_{2.5}$ **(Hamilton)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1745***	-0.2438***	-0.2185***	-0.0973***
	(0.0293)	(0.0224)	(0.0223)	(0.0166)
Hydro	0.0554**	-0.0124	0.0365	0.0092
	(0.0245)	(0.0335)	(0.0428)	(0.0178)
Nuclear	-0.1201***	-0.2603***	-0.2455***	-0.0962***
	(0.0114)	(0.0173)	(0.0273)	(0.0135)
Other	0.4748***	0.4643**	0.6495***	0.2092**
	(0.1755)	(0.1955)	(0.1708)	(0.0701)
Wind	-0.0328	-0.2119***	-0.2029***	-0.1115***
	(0.0241)	(0.0265)	(0.0265)	(0.0207)
Total	0.0003***	0.000006	0.0001***	0.0002***
	(0.00004)	(0.00005)	(0.00007)	(0.00003)
Lag3-$PM_{2.5}$	NA	NA	NA	0.4973***
				(0.0168)
Lag6-$PM_{2.5}$	NA	NA	NA	0.1579***
				(0.0128)
Temperature	0.2867***	0.3207***	0.3009***	0.0415***
	(0.0128)	(0.013)	(0.0134)	(0.0119)
Relative Humidity	0.1477***	0.1546***	0.1476***	0.0608***
	(0.0051)	(0.0073)	(0.0064)	(0.0029)
Constant	-5.012***	7.6445***	3.5166***	-0.7851
	(2.48)	(3.4938)	(3.9928)	(1.6253)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	22929	22929	22929	22506
R^2	0.1116	0.14	0.1410	0.4571

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.16: GLS & Time-Series Estimates of Fuel Mix on NO_x (Ottawa)

Dependent Var: NO_x **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.1849***	0.1456***	0.1481***	0.1059***	0.0701***
	(0.0269)	(0.0278)	(0.0289)	(0.0249)	(0.0155)
Hydro	0.1608***	0.1187***	0.0828***	0.0523**	0.1342***
	(0.0230)	(0.0268)	(0.0266)	(0.0266)	(0.0139)
Nuclear	0.0351***	-0.0124	-0.0076	-0.0069	-0.0217*
	(0.0118)	(0.0108)	(0.0117)	(0.0118)	(0.0117)
Other	0.5832***	0.4940***	0.3635***	-0.0445	-0.3338***
	(0.0892)	(0.0654)	(0.0686)	(0.1271)	(0.0793)
Wind	-0.0707***	-0.1376***	-0.1936***	-0.2061***	-0.1329
	(0.0259)	(0.0312)	(0.0311)	(0.0353)	(0.0166)
Total	0.0003***	0.0002***	0.0002***	0.00008***	0.0001***
	(0.00007)	(0.00008)	(0.00006)	(0.00006)	(0.00002)
Lag3-NO_x	NA	NA	NA	NA	0.5130***
					(0.0121)
Lag6-NO_x	NA	NA	NA	NA	0.0545***
					(0.0082)
Temperature	-0.2611***	-0.2633***	-0.2078***	-0.2170***	-0.1609***
	(0.0214)	(0.0221)	(0.0324)	(0.0353)	(0.0059)
Relative Humidity	0.1302***	0.1308***	0.1355***	0.1320***	0.0948***
	(0.0067)	(0.0070)	(0.0071)	(0.0079)	(0.0019)
Constant	-13.1733***	-8.2599***	-6.9303**	-2.7445	-6.8149***
	(2.5254)	(2.8086)	(2.7666)	(2.6106)	(1.3200)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66241	66241	66241	66241	65283
R^2	0.1591	0.1610	0.1634	0.1755	0.4296

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.17: GLS & Time-Series Estimates of Fuel Mix on O_3 (Ottawa)

Dependent Var: O_3 **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	-0.3082***	-0.3347***	-0.1372***	-0.1030***	-0.0689***
	(0.0175)	(0.0149)	(0.0213)	(0.0207)	(0.0113)
Hydro	0.0362	0.0514**	-0.0674***	-0.0470*	-0.0877***
	(0.0346)	(0.0220)	(0.0216)	(0.0251)	(0.0116)
Nuclear	-0.2670***	-0.2883***	-0.1006***	-0.1040***	-0.0427***
	(0.0150)	(0.0108)	(0.0102)	(0.0104)	(0.0100)
Other	0.1591	-0.5237***	-0.2461***	0.1955**	0.5659***
	(0.2029)	(0.0796)	(0.0775)	(0.0867)	(0.0790)
Wind	0.2623***	0.2953***	0.4562***	0.4654***	0.2433***
	(0.0179)	(0.0309)	(0.0217)	(0.0231)	(0.0134)
Total	0.0007***	0.0007***	0.0006***	0.0008***	0.0003***
	(0.00005)	(0.00005)	(0.00004)	(0.00007)	(0.00001)
Lag3-O_3	NA	NA	NA	NA	0.5972***
					(0.0049)
Lag6-O_3	NA	NA	NA	NA	-.0337***
					(0.0044)
Temperature	0.1227***	0.1258***	0.2527***	0.2619***	0.1845***
	(0.0181)	(0.0178)	(0.0162)	(0.0150)	(0.0040)
Relative Humidity	-0.3403***	-0.3413***	-0.3090***	-0.3065***	-0.1945***
	(0.0073)	(0.0078)	(0.0089)	(0.0102)	(0.0017)
Constant	53.5449***	54.8932***	39.2870***	35.5441***	20.3373***
	(3.0154)	(2.0905)	(2.4833)	(2.3074)	(1.0984)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66380	66380	66380	66380	65421
R^2	0.3766	0.3855	0.4512	0.4659	0.6900

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.18: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Ottawa)

Dependent Var: $PM_{2.5}$ **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.0646***	0.0358***	0.0628***	0.0775***	0.0098*
	(0.0054)	(0.0067)	(0.0065)	(0.0055)	(0.0052)
Hydro	0.0582***	-0.0403***	-0.0678***	-0.0310**	0.0069
	(0.0056)	(0.0065)	(0.0064)	(0.0150)	(0.0057)
Nuclear	0.0847***	0.0081	0.0275***	0.0288***	-0.0146***
	(0.0066)	(0.0070)	(0.0070)	(0.0071)	(0.0047)
Other	-0.1526	-0.0629	-0.0546	0.1041	-0.1602***
	(0.1326)	(0.1293)	(0.1219)	(0.1234)	(0.0373)
Wind	0.1770***	0.0847***	0.0775***	0.0955***	0.0045
	(0.0083)	(0.0094)	(0.0094)	(0.0085)	(0.0062)
Total	0.0004***	0.0003***	0.0003***	0.0004***	0.0001***
	(0.00001)	(0.00001)	(0.00001)	(0.00003)	(8.17e-06)
Lag3-$PM_{2.5}$	NA	NA	NA	NA	0.6521***
					(0.0110)
Lag6-$PM_{2.5}$	NA	NA	NA	NA	0.1072***
					(0.0095)
Temperature	0.0493***	0.0464***	0.1147***	0.1282***	0.0142***
	(0.0040)	(0.0038)	(0.0055)	(0.0058)	(0.0019)
Relative Humidity	0.0687***	0.0684***	0.0756***	0.0686***	0.0293***
	(0.0020)	(0.0021)	(0.0021)	(0.0021)	(0.0008)
Constant	-15.5207***	-5.6888***	-7.1423***	-10.5370***	-2.5757***
	(0.8431)	(0.9196)	(0.8728)	(1.2932)	(0.5271)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	65944	65944	65944	65944	65133
R^2	0.0887	0.1144	0.1361	0.1466	0.6129

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.19: GLS & Time-Series Estimates of Fuel Mix on NO_x (Ottawa)

Dependent Var: NO_x **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	0.0689***	0.0471***	0.0161	0.0225*
	(0.0084)	(0.0148)	(0.0132)	(0.0118)
Hydro	-0.0122	-0.0102	-0.0540*	-0.0063
	(0.0126)	(0.0222)	(0.0281)	(0.0117)
Nuclear	-0.0274***	-0.0690***	-0.0800***	-0.0420***
	(0.0087)	(0.0096)	(0.0116)	(0.0101)
Other	0.0035	-0.0254	-0.2448**	-0.3718***
	(0.1069)	(0.0820)	(0.1029)	(0.0566)
Wind	0.0345	-0.0584**	-0.0571**	-0.0627***
	(0.0226)	(0.0227)	(0.0237)	(0.0147)
Total	-0.00006**	-0.0001***	-0.0003***	-0.00006***
	(0.00002)	(0.00002)	(0.00006)	(0.00002)
Lag3-NO_x	NA	NA	NA	0.4012***
				(0.0137)
Lag6-NO_x	NA	NA	NA	0.0410***
				(0.0097)
Temperature	-0.1809***	-0.1708***	-0.1320***	-0.1511***
	(0.0290)	(0.0284)	(0.0357)	(0.0085)
Relative Humidity	0.0171***	0.0235***	0.0296***	0.0300***
	(0.0044)	(0.0043)	(0.0051)	(0.0016)
Constant	8.8258***	10.8809***	15.5923***	6.5144***
	(1.5067)	(1.9568)	(2.6090)	(1.1528)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23220	23220	23220	22866
R^2	0.0895	0.1036	0.1420	0.2889

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.20: GLS & Time-Series Estimates of Fuel Mix on O_3 (Ottawa)

Dependent Var: O_3 **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1815***	-0.0445	-0.0054	-0.0090
	(0.0227)	(0.0324)	(0.0280)	(0.0220)
Hydro	0.1950***	0.4866***	0.6255***	0.3059***
	(0.0284)	(0.0476)	(0.0444)	(0.0216)
Nuclear	-0.4083***	-0.2614***	-0.2259***	-0.0933***
	(0.0163)	(0.0179)	(0.0240)	(0.0175)
Other	0.3835	-0.0697	0.2400**	0.3829***
	(0.2497)	(0.0638)	(0.1125)	(0.1187)
Wind	0.8592***	1.1575***	1.1588***	0.6243***
	(0.0458)	(0.0457)	(0.0447)	(0.0266)
Total	-0.0002**	-0.00018***	0.0001	-0.0001***
	(0.00009)	(0.0001)	(0.0001)	(0.00003)
Lag3-O_3	NA	NA	NA	0.5507***
				(0.0080)
Lag6-O_3	NA	NA	NA	-0.0324***
				(0.0071)
Temperature	0.7984***	0.8750***	0.8836***	0.5963***
	(0.0328)	(0.0345)	(0.0388)	(0.0144)
Relative Humidity	-0.2064***	-0.1973***	-0.2090***	-0.1454***
	(0.0118)	(0.0127)	(0.0142)	(0.0029)
Constant	50.3886	29.2003***	16.1560***	11.1037***
	(2.2088)	(3.6286)	(3.2890)	(2.0113)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23410	23410	23410	23076
R^2	0.4738	0.4982	0.5159	0.7099

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.21: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Ottawa)

Dependent Var: $PM_{2.5}$ **(Ottawa)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.1443***	-0.1363***	-0.1096***	-0.0278**
	(0.0093)	(0.0143)	(0.0126)	(0.0114)
Hydro	-0.0941***	-0.1035***	0.0174	-0.0092
	(0.0094)	(0.0195)	(0.0312)	(0.0105)
Nuclear	-0.1181***	-0.1704***	-0.1315***	-0.0367***
	(0.0114)	(0.0142)	(0.0143)	(0.0092)
Other	0.0023	-0.1333	0.0238	-0.2191***
	(0.1219)	(0.1729)	(0.1536)	(0.0641)
Wind	0.0678***	0.0387***	0.0763***	0.0338***
	(0.0198)	(0.0147)	(0.0158)	(0.0120)
Total	-0.0001***	-0.0003***	-0.00005	-0.00007***
	(0.00002)	(0.00003)	(0.00007)	(0.00001)
Lag3-$PM_{2.5}$	NA	NA	NA	0.6536***
				(0.0246)
Lag6-$PM_{2.5}$	NA	NA	NA	0.0865***
				(0.0203)
Temperature	0.3430***	0.3677***	0.3960***	0.0937***
	(0.0149)	(0.0141)	(0.0175)	(0.0087)
Relative Humidity	0.0699***	0.0746***	0.0616***	0.0242***
	(0.0055)	(0.0062)	(0.0067)	(0.0019)
Constant	7.4568***	12.2777***	1.5844	1.6768*
	(1.6130)	(2.3652)	(3.1374)	(1.0143)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23095	23095	23095	22786
R^2	0.1143	0.1383	0.1699	0.5828

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.22: GLS & Time-Series Estimates of Fuel Mix on NO_x (Sarnia)

Dependent Var: NO_x **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	0.114***	0.0462	0.0403*	0.0388	0.0385**
	(0.0343)	(0.037)	(0.0305)	(0.0317)	(0.0151)
Hydro	0.1359***	0.0366	-0.0787	0.008	0.0034**
	(0.0337)	(0.0387)	(0.0468)	(0.0356)	(0.0146)
Nuclear	0.0685***	0.0082	-0.023*	-0.019**	0.0025
	(0.0117)	(0.0166)	(0.0148)	(0.0126)	(0.0125)
Other	-0.3687**	0.0583	0.0383	-0.1557	-0.4335***
	(0.1575)	(0.1336)	(0.1166)	(0.1016)	(0.0718)
Wind	-0.1271**	-0.2231***	-0.4342***	-0.4027***	-0.2436***
	(0.0555)	(0.0702)	(0.0604)	(0.0603)	(0.0175)
Total	0.0005***	0.0004***	0.0001**	0.0002***	0.00003*
	(0.00006)	(0.00007)	(0.00007)	(0.00007)	(0.00002)
Lag3-NO_x	NA	NA	NA	NA	0.4533***
					(0.0172)
Lag6-NO_x	NA	NA	NA	NA	0.0667***
					(0.0082)
Temperature	0.0155***	0.0132***	0.0009	0.0060	-0.0052*
	(0.004)	(0.0037)	(0.0038)	(0.0047)	(0.0030)
Relative Humidity	0.0753***	0.0868***	0.0622***	0.0438***	0.0524***
	(0.0070)	(0.0087)	(0.0098)	(0.0088)	(0.0022)
Constant	-11.732***	-4.4345	8.4922***	6.675***	1.9094
	(2.3866)	(2.9931)	(2.2648)	(1.8053)	(1.3901)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	65654	65654	65654	65654	63255
R^2	0.0216	0.0281	0.0557	0.0781	0.2945

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.23: GLS & Time-Series Estimates of Fuel Mix on O_3 (Sarnia)

Dependent Var: O_3 **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	-0.1111***	-0.3202***	-0.129***	-0.1073***	-0.0595***
	(0.0368)	(0.0398)	(0.0384)	(0.0277)	(0.0129)
Hydro	-0.0305	-0.0711*	-0.0288	-0.1948***	-0.0391***
	(0.033)	(0.0452)	(0.0481)	(0.0484)	(0.0132)
Nuclear	-0.3237***	-0.5238***	-0.2414***	-0.2530***	-0.1343***
	(0.0137)	(0.0371)	(0.0159)	(0.0152)	(0.0115)
Other	1.5098***	1.7106***	1.7648***	2.0814***	1.8194***
	(0.2753)	(0.3559)	(0.3049)	(0.2415)	(0.1008)
Wind	-0.0616	-0.3071**	0.2559**	0.1816*	0.097***
	(0.0881)	(0.143)	(0.092)	(0.1029)	(0.0151)
Total	0.0002*	0.0002**	0.0011***	0.0007***	0.0005***
	(0.00001)	(0.00001)	(0.0001)	(0.0001)	(0.00002)
Lag3-O_3	NA	NA	NA	NA	0.7286***
					(0.005)
Lag6-O_3	NA	NA	NA	NA	-0.1424***
					(0.0047)
Temperature	-0.0098*	-0.0006	0.0241***	0.0104***	0.0287***
	(0.0056)	(0.006)	(0.003)	(0.0032)	(0.0031)
Relative Humidity	-0.141***	-0.1741***	-0.1182***	-0.0617***	-0.0787***
	(0.0063)	(0.011)	(0.0130)	(0.011)	(0.0021)
Constant	56.1362***	68.1397***	24.4753***	28.5888***	10.8127***
	(3.1432)	(5.6431)	(2.5044)	(3.6390)	(1.3340)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66500	66500	66500	66500	65365
R^2	0.1272	0.1463	0.273	0.3367	0.6049

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.24: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Sarnia)

Dependent Var: $PM_{2.5}$ **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**	**Reg (5)**
Independent Var:					
Gas	-0.0744***	-0.1084***	-0.1011***	-0.0748***	-0.0146**
	(0.0141)	(0.0104)	(0.0106)	(0.0106)	(0.0078)
Hydro	-0.2728***	-0.2775***	-0.2527***	-0.1959***	-0.0468***
	(0.0148)	(0.0101)	(0.0104)	(0.011)	(0.0081)
Nuclear	-0.127***	-0.1326***	-0.1262***	-0.1264***	-0.0279***
	(0.0122)	(0.008)	(0.0092)	(0.0091)	(0.007)
Other	-0.2122*	-0.4347***	-0.3914***	-0.1114	-0.3303***
	(0.1291)	(0.1321)	(0.1323)	(0.1331)	(0.0569)
Wind	-0.3472***	-0.3216***	-0.2812***	-0.2552***	-0.1071***
	(0.0117)	(0.0121)	(0.0126)	(0.0126)	(0.0088)
Total	0.00006***	0.0001***	0.0001***	0.0003***	0.00005***
	(0.00001)	(0.00002)	(0.00002)	(0.00005)	(0.00001)
Lag3-$PM_{2.5}$	NA	NA	NA	NA	0.6046***
					(0.0086)
Lag6-$PM_{2.5}$	NA	NA	NA	NA	0.1464***
					(0.0068)
Temperature	0.0024*	0.0029**	0.0024*	0.0077***	-0.0011
	(0.0013)	(0.0013)	(0.0013)	(0.0018)	(0.0017)
Relative Humidity	0.0235***	0.0206***	0.0264***	0.014***	0.0178***
	(0.0024)	(0.0024)	(0.0028)	(0.0031)	(0.0011)
Constant	22.48***	22.7993***	20.8755***	16.0541***	3.4813***
	(1.0374)	(0.9502)	(1.0397)	(1.3282)	(0.7618)
Year	NO	YES	YES	YES	YES
Season	NO	NO	YES	YES	YES
Day of Week	NO	NO	NO	YES	YES
Hour	NO	NO	NO	YES	NO
Observation	66276	66276	66276	66276	65605
R^2	0.0477	0.0558	0.0581	0.0714	0.5409

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.25: OLS & Time-Series Estimates of Fuel Mix on NO_x (Sarnia)

Dependent Var: NO_x **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	0.0724***	-0.0748***	-0.0599***	-0.0693***
	(0.0285)	(0.0135)	(0.013)	(0.0209)
Hydro	0.0764***	-0.0632***	-0.0868*	-0.1467***
	(0.0237)	(0.0234)	(0.0453)	(0.0226)
Nuclear	-0.0124	-0.1705***	-0.1687***	-0.1149***
	(0.0126)	(0.0213)	(0.0211)	(0.0191)
Other	-0.3105***	-0.2182***	-0.3363**	-0.6142***
	(0.1571)	(0.1065)	(0.1572)	(0.1016)
Wind	-0.158***	-0.3317***	-0.3033***	-0.2675***
	(0.0532)	(0.0818)	(0.0796)	(0.0256)
Total	0.00005	-0.0001	-0.0002	-0.0004***
	(0.00005)	(0.00008)	(0.0001)	(0.00003)
Lag3-NO_x	NA	NA	NA	0.3958***
				(0.0157)
Lag6-NO_x	NA	NA	NA	0.0656***
				(0.0114)
Temperature	0.0069**	0.0062*	0.0051	-0.004***
	(0.0033)	(0.0034)	(0.0035)	(0.0038)
Relative Humidity	0.0348***	0.0322***	0.0372***	0.0423***
	(0.0043)	(0.0043)	(0.0077)	(0.0029)
Constant	4.4489***	21.2696***	22.9265***	20.6748***
	(1.5350)	(3.1382)	(4.7203)	(2.1532)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	22976	22976	22976	22610
R^2	0.0062	0.0204	0.0740	0.2278

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “coal”. Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.26: GLS & Time-Series Estimates of Fuel Mix on O_3 (Sarnia)

Dependent Var: O_3 **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.0657**	-0.1751***	-0.1222***	-0.0407
	(0.0238)	(0.0388)	(0.0375)	(0.0294)
Hydro	-0.0084	0.513***	0.4691***	0.3328***
	(0.039)	(0.0667)	(0.0773)	(0.0298)
Nuclear	-0.4107***	-0.2132***	-0.2519***	-0.1002***
	(0.0109)	(0.031)	(0.0396)	(0.0233)
Other	1.9199***	1.3734***	2.2147***	1.8491***
	(0.1761)	(0.1892)	(0.2501)	(0.1514)
Wind	0.4601***	0.5835***	0.5046***	0.2764***
	(0.1000)	(0.1567)	(0.145)	(0.0358)
Total	0.0013***	0.0026***	0.0023***	0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.00005)
Lag3-O_3	NA	NA	NA	0.6448***
				(0.0071)
Lag6-O_3	NA	NA	NA	-0.1377***
				(0.0074)
Temperature	0.0188**	0.0151***	0.0108**	0.0213***
	(0.0047)	(0.0048)	(0.0051)	(0.005)
Relative Humidity	-0.0414***	-0.058***	-0.0419***	-0.0695***
	(0.0072)	(0.008)	(0.0002)	(0.0044)
Constant	35.6549***	-5.9547***	-5.4177*	-11.2565
	(2.3764)	(5.5151)	(3.8846)	(2.8373)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23336	23336	23336	22957
R^2	0.2922	0.3309	0.3967	0.6013

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.27: GLS & Time-Series Estimates of Fuel Mix on $PM_{2.5}$ (Sarnia)

Dependent Var: $PM_{2.5}$ **(Sarnia)**	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.2352***	-0.2844***	-0.1944***	-0.0928***
	(0.0199)	(0.0237)	(0.0234)	(0.0172)
Hydro	-0.4961***	-0.4881***	-0.3181***	-0.1451***
	(0.0153)	(0.0325)	(0.0538)	(0.0172)
Nuclear	-0.3312***	-0.3052***	-0.2693***	-0.0985***
	(0.00926)	(0.0293)	(0.0291)	(0.0141)
Other	-0.0233	-0.3249*	0.1867	-0.4019***
	(0.1809)	(0.1716)	(0.1579)	(0.0809)
Wind	-0.4943***	-0.3472***	-0.2992***	-0.1443***
	(0.0196)	(0.0265)	(0.0265)	(0.019)
Total	-0.00006	0.00007***	0.0005***	0.000001
	(0.00004)	(0.00006)	(0.0001)	(0.00002)
Lag3-$PM_{2.5}$	NA	NA	NA	0.5751***
				(0.0141)
Lag6-$PM_{2.5}$	NA	NA	NA	0.1437***
				(0.0117)
Temperature	0.0016	0.0016	0.0044	-0.0034
	(0.0022)	(0.0022)	(0.0026)	(0.0027)
Relative Humidity	0.0384***	0.0291***	0.0204***	0.0123***
	(0.0026)	(0.0026)	(0.0054)	(0.0024)
Constant	43.6627***	41.3153***	23.7450***	12.7765***
	(1.5077)	(3.5898)	(4.9936)	(1.6104)
Year	NO	YES	YES	YES
Day of Week	NO	NO	YES	YES
Hour	NO	NO	YES	NO
Observation	23268	23268	23268	22988
R^2	0.1299	0.1582	0.1913	0.5575

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “coal”. Regressions are based on the hourly data from May to August of 2009 to 2016.

Table 3.28: GLS Regressions of Pollutants in Toronto (Sensitivity Analysis)

Dependent Var:	NO_X		O_3		$PM_{2.5}$	
(Toronto)	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**
Independent Var:						
Gas	0.1384**	0.1384***	-0.062	-0.062***	0.005	0.005
	(0.0574)	(0.0248)	(0.048)	(0.0219)	(0.0294)	(0.0114)
Hydro	0.008	0.008	-0.1324***	-0.1324***	-0.0486*	-0.0486***
	(0.0555)	(0.0247)	(0.0495)	(0.0228)	(0.0291)	(0.0117)
Nuclear	-0.0103	-0.0103	-0.1628***	-0.1628***	-0.0348	-0.0348***
	(0.0486)	(0.0206)	(0.0442)	(0.0194)	(0.0258)	(0.0101)
Other	0.2552	0.2552*	1.5162***	1.5162***	0.3716**	0.3716***
	(0.2864)	(0.1343)	(0.3092)	(0.1500)	(0.1601)	(0.0731)
Wind	-0.9733***	-0.9733***	0.7074***	0.7074***	-0.1573***	-0.1573***
	(0.0610)	(0.0257)	(0.0560)	(0.0234)	(0.0329)	(0.0120)
Total	0.0001	0.0001**	0.0011***	0.0011***	0.0005***	0.0005***
	(0.00008)	(0.00004)	(0.00008)	(0.00004)	(0.00004)	(0.00002)
Temperature	-0.1176***	-0.1176***	0.4966***	0.4966***	0.2717***	0.2717***
	(0.0236)	(0.0096)	(0.0205)	(0.0089)	(0.0115)	(0.0043)
Relative Humidity	0.0845***	0.0845***	-0.2175***	-0.2175***	0.0738***	0.0738***
	(0.0080)	(0.0034)	(0.0072)	(0.0030)	(0.0043)	(0.0015)
Constant	18.7149***	18.7149***	21.1235***	21.1235***	-8.1645***	-8.1645***
	(5.1392)	(2.2040)	(4.8619)	(2.1444)	(2.7704)	(1.1220)
Year	YES	YES	YES	YES	YES	YES
Season	YES	YES	YES	YES	YES	YES
Day of Week	YES	YES	YES	YES	YES	YES
Hour	YES	YES	YES	YES	YES	YES
Observation	66614	66614	66885	66885	66288	66288
R^2	0.2218	0.2218	0.4682	0.4682	0.1936	0.1936

Note: Standard errors are in parentheses and clustered at the day level in Reg (1). Reg (2) considers Newey-West standard error structure. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “coal”. Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.29: GLS Regressions of Pollutants in Hamilton (Sensitivity Analysis)

Dependent Var:	NO_X		O_3		$PM_{2.5}$	
(Hamilton)	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**
Independent Var:						
Gas	0.1716***	0.1716***	-0.0571	-0.0571***	-0.0476	-0.0476***
	(0.0502)	(0.0218)	(0.0469)	(0.0199)	(0.0305)	(0.0123)
Hydro	0.1825***	0.1825***	-0.2326***	-0.2326***	-0.0763**	-0.0763***
	(0.0481)	(0.0210)	(0.0490)	(0.0217)	(0.0311)	(0.0131)
Nuclear	0.0597	0.0597***	-0.1645***	-0.1645***	-0.0797***	-0.0797***
	(0.0422)	(0.0175)	(0.0436)	(0.0178)	(0.0271)	(0.0109)
Other	0.2641	0.2641***	0.9447***	0.9447***	0.2049	0.2049***
	(0.2323)	(0.1005)	(0.2540)	(0.1193)	(0.1614)	(0.0731)
Wind	-0.7152***	-0.7152***	0.4964***	0.4964***	-0.254***	-0.254***
	(0.0514)	(0.0214)	(0.0552)	(0.0219)	(0.0341)	(0.0129)
Total	-0.00005	-0.00005*	0.0011***	0.0011***	0.0004***	0.0004***
	(0.00007)	(0.00003)	(0.00009)	(0.00004)	(0.00004)	(0.00002)
Temperature	-0.2454***	-0.2454***	0.5174***	0.5174***	0.2182***	0.2182***
	(0.0198)	(0.0081)	(0.0192)	(0.0078)	(0.0114)	(0.0043)
Relative Humidity	0.1954***	0.1954***	-0.3002***	-0.3002***	0.1172***	0.1173***
	(0.0077)	(0.0032)	(0.0073)	(0.0029)	(0.0047)	(0.0018)
Constant	-6.1098	-6.1098	35.2043***	35.2043***	-5.2842*	-5.2842***
	(4.5905)	(1.9348)	(4.8609)	(2.0494)	(2.9378)	(1.2191)
Year	YES	YES	YES	YES	YES	YES
Season	YES	YES	YES	YES	YES	YES
Day of Week	YES	YES	YES	YES	YES	YES
Hour	YES	YES	YES	YES	YES	YES
Observation	66256	66256	66599	66599	66186	66186
R^2	0.2200	0.2200	0.5279	0.5279	0.1767	0.1767

Note: Standard errors are in parentheses and clustered at the day level in Reg (1). Reg (2) considers Newey-West standard error structure. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is “coal”. Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.30: GLS Regressions of Pollutants in Ottawa (Sensitivity Analysis)

Dependent Var:	NO_X		O_3		$PM_{2.5}$	
(Ottawa)	**Reg (1)**	**Reg(2)**	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**
Independent Var:						
Gas	0.1059*	0.1059***	-0.1030**	-0.1030***	0.0775***	0.0775***
	(0.0568)	(0.0220)	(0.0481)	(0.0194)	(0.0264)	(0.0102)
Hydro	0.0523	0.0523**	-0.0470	-0.0470**	-0.0310	-0.0310**
	(0.0501)	(0.0204)	(0.0489)	(0.0210)	(0.0290)	(0.0113)
Nuclear	-0.0069	-0.0069	-0.1040**	-0.1040***	0.0288	0.0288***
	(0.0410)	(0.0156)	(0.0435)	(0.0173)	(0.0225)	(0.0088)
Other	-0.0445	-0.0445	0.1955	0.1955*	0.1041	0.1041*
	(0.1839)	(0)	(0.2519)	(0.1072)	(0.1306)	(0.0593)
Wind	-0.2061***	-0.2061***	0.4654***	0.4654***	0.0955***	0.0955***
	(0.0565)	(0.0210)	(0.0561)	(0.0215)	(0.0294)	(0)
Total	0.00008	0.00008**	0.0008***	0.0008***	0.0004***	0.0004***
	(0.00007)	(0.00003)	(0.00008)	(0.00003)	(0.00004)	(0.0593)
Temperature	-0.2170***	-0.2170***	0.2619***	0.2619***	0.1282***	0.1282***
	(0.0210)	(0.0082)	(0.0185)	(0.0074)	(0.0092)	(0.0032)
Relative Humidity	0.1320***	0.1320***	-0.3065***	-0.3065***	0.0686***	0.0686***
	(0.0064)	(0.0028)	(0.0065)	(0.0026)	(0.0037)	(0.0013)
Constant	-2.7445	-2.7445	35.5441***	35.5441***	-10.5370***	-10.5370***
	(4.6128)	(1.8127)	(4.7596)	(1.9485)	(2.5479)	(1.0274)
Year	YES	YES	YES	YES	YES	YES
Season	YES	YES	YES	YES	YES	YES
Day of Week	YES	YES	YES	YES	YES	YES
Hour	YES	YES	YES	YES	YES	YES
Observation	66241	66241	66380	66380	65944	65944
R^2	0.1755	0.1755	0.4659	0.4659	0.1466	0.1466

Note: Standard errors are in parentheses and clustered at the day level in Reg (1). Reg (2) considers Newey-West standard error structure. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.31: GLS Regressions of Pollutants in Sarnia (Sensitivity Analysis)

Dependent Var:	NO_X		O_3		$PM_{2.5}$	
(Sarnia)	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**	**Reg (1)**	**Reg (2)**
Independent Var:						
Gas	0.0388	0.0388*	-0.1073**	-0.1073***	-0.0748*	-0.0748***
	(0.0458)	(0.0204)	(0.0539)	(0.0253)	(0.0382)	(0.0149)
Hydro	0.008	0.008	-0.1948***	-0.1948***	-0.1959***	-0.1959***
	(0.0425)	(0.0201)	(0.0536)	(0.0262)	(0.0386)	(0.0158)
Nuclear	-0.019	-0.019	-0.2530***	-0.2530***	-0.1264***	-0.1264***
	(0.0369)	(0.0171)	(0.0462)	(0.0220)	(0.0340)	(0.0136)
Other	-0.1557	-0.1557	2.0814***	2.0814***	-0.1114	-0.1114
	(0.2752)	(0.1125)	(0.3535)	(0.1580)	(0.1951)	(0.0798)
Wind	-0.4027***	-0.4027***	0.1816***	0.1816***	-0.2552***	-0.2552***
	(0.0526)	(0.0221)	(0.0599)	(0.0266)	(0.0413)	(0.0156)
Total	0.0002***	0.0002***	0.0007***	0.0007***	0.0003***	0.0003***
	(0.00007)	(0.00003)	(0.00009)	(0.00004)	(0.00005)	(0.00002)
Temperature	0.006	0.006	0.0104	0.0104**	0.0077	0.0077***
	(0.0103)	(0.0038)	(0.0129)	(0.0051)	(0.0089)	(0.0027)
Relative Humidity	0.0438***	0.0438***	-0.0617***	-0.0617***	0.0146***	0.0146***
	(0.0071)	(0.0032)	(0.0085)	(0.0033)	(0.0054)	(0.0019)
Constant	6.675	6.675***	28.5888***	28.5888***	17.3329***	17.3329***
	(4.1506)	(1.9093)	(5.1093)	(2.4349)	(3.6516)	(1.4841)
Year	YES	YES	YES	YES	YES	YES
Season	YES	YES	YES	YES	YES	YES
Day of Week	YES	YES	YES	YES	YES	YES
Hour	YES	YES	YES	YES	YES	YES
Observation	65654	65654	66500	66500	66276	66276
R^2	0.0781	0.0781	0.3367	0.3367	0.0714	0.0714

Note: Standard errors are in parentheses and clustered at the day level in Reg (1). Reg (2) considers Newey-West standard error structure. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the hourly data from January 2009 to December 2016 (excluding August 2014 to December 2014).

Table 3.32: Marginal Effects from Probit Regressions of Fuel Mix on the Likelihood of Smog days (March- October)

Dependent Var: Smog (58 Days)	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	0.0014	0.00004	-6.02e-08	-3.86e-06
	(0.0014)	(0.00009)	(0.00000)	(0.00001)
Hydro	-0.0048***	-0.00001	1.93e-07*	7.12e-06
	(0.0011)	(0.00006)	(0.00000)	(0.00001)
Nuclear	-0.0004	0.00004	1.67e-07**	3.83e-06
	(0.0009)	(0.00007)	(0.00000)	(0.00001)
Other	0.0269***	0.0013	7.05e-07	0.00002
	(0.0091)	(0.0017)	(0.00000)	(0.00006)
Wind	-0.0054**	-1.27e-07	-1.02e-07	-1.33e-06
	(0.0021)	(0.0001)	(0.00000)	(0.00000)
Total	NO	-3.14e-07*	2.05e-10	9.76e-09
		(0.00000)	(0.00000)	(0.00000)
Temperature	NO	0.0016	2.22e-06	0.00005
		(0.0017)	(0.00000)	(0.0001)
Rel. Humidity	NO	-0.00007	-3.26e-08	-2.52e-07
		(0.00009)	(0.00000)	(0.00000)
Exchange Rate	NO	NO	NO	YES
Unemployment Rate	NO	NO	NO	YES
Month	NO	NO	YES	NO
Year	NO	NO	YES	YES
Constant	-0.0531	-5.5269**	-27.6736***	-33.5714***
	(1.4906)	(2.2871)	(4.9350)	(9.1168)
Observation	1409	1409	1409	1409

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the daily data from March to October of 2009 to 2014.

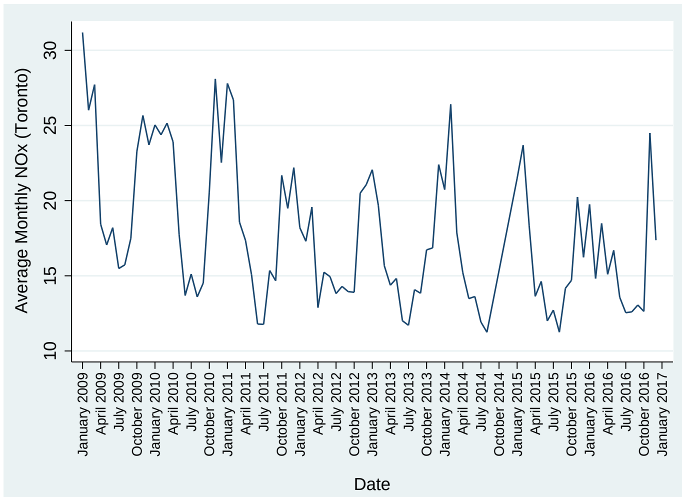
Table 3.33: Marginal Effects from Probit Regressions of Fuel Mix on the Likelihood of Smog days (June-August)

Dependent Var: Smog (38 Days)	**Reg (1)**	**Reg (2)**	**Reg (3)**	**Reg (4)**
Independent Var:				
Gas	-0.0031	-0.0011	-0.0005	-0.0004
	(0.003)	(0.0012)	(0.0005)	(0.0004)
Hydro	-0.0094***	-0.0023	0.0002	0.0002
	(0.0035)	(0.0014)	(0.0003)	(0.0003)
Nuclear	-0.0033	0.0015*	0.0002	0.0001
	(0.002)	(0.001)	(0.0001)	(0.0001)
Other	0.091***	0.0217**	0.0012	0.001
	(0.0273)	(0.014)	(0.0014)	(0.0012)
Wind	-0.0136*	-0.0056*	-0.0005	-0.0004
	(0.0073)	(0.0032)	(0.0006)	(0.0004)
Total	NO	-6.38e-06	4.46e-07	3.82e-07
		(0..00000)	(0.00000)	(0..00000)
Daily Avg. Temperature	NO	0.0374***	0.0041	0.0034
		(0.0123)	(0.0032)	(0.0027)
Daily Avg rel. Humidity	NO	-0.0002	0.0001	0.0001
		(0.0011)	(0.0001)	(0.0001)
Exchange Rate	NO	NO	NO	YES
Unemployment Rate	NO	NO	NO	YES
Month	NO	NO	YES	NO
Year	NO	NO	YES	YES
Constant	2.0038	-8.1565**	-25.7162***	-35.4007**
	(2.098)	(3.8729)	(7.9552)	(14.4523)
Observation	522	522	522	522

Note: Robust standard errors are in parentheses. ***,** and * indicate statistical significance level at 1 percent, 5 percent and 10 percent, respectively. The omitted category for fuel type is "coal". Regressions are based on the daily data from June to August of 2009 to 2014.

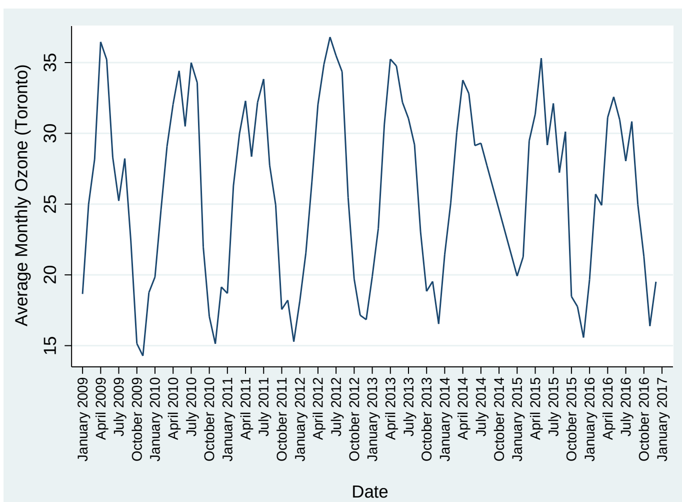
3.8 Figures

Figure 3.1: Average Monthly NO_x in Toronto (2009-2016)



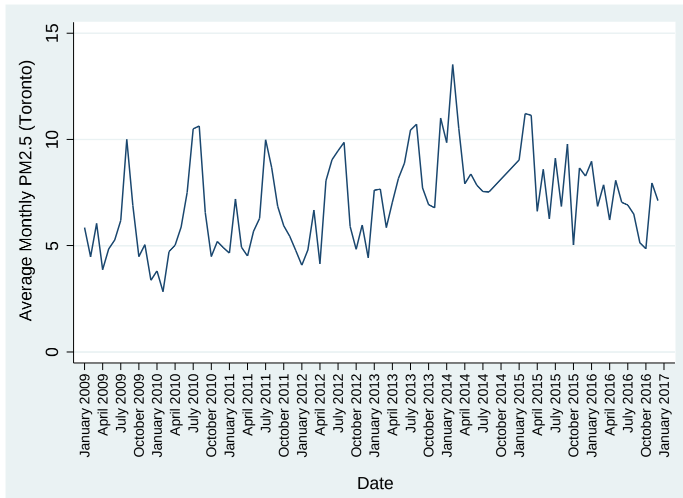
Source: Author's own calculations.

Figure 3.2: Average Monthly O_3 in Toronto (2009-2016)



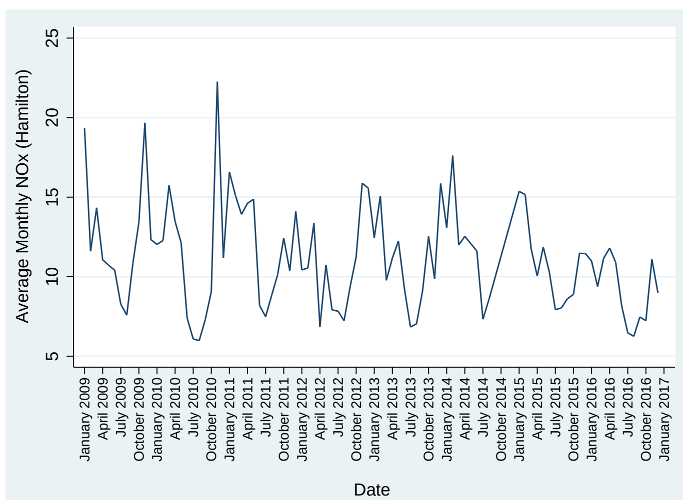
Source: Author's own calculations.

Figure 3.3: Average Monthly $PM_{2.5}$ in Toronto (2009-2016)



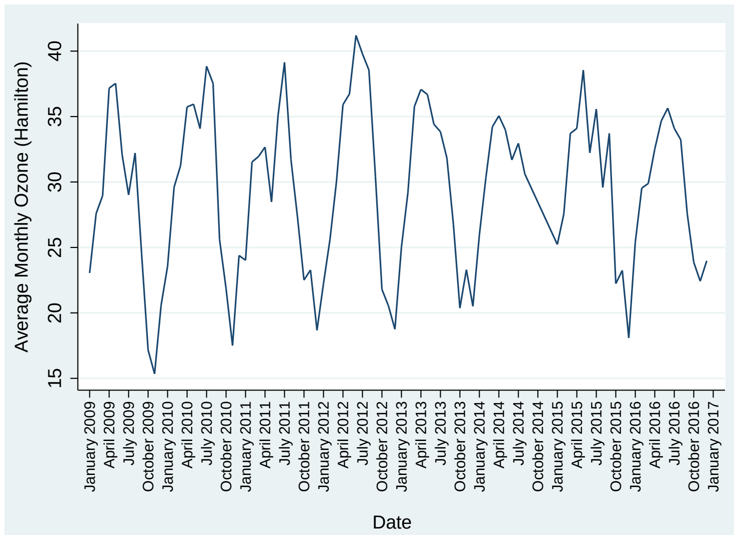
Source: Author's own calculations.

Figure 3.4: Average Monthly NO_x in Hamilton (2009-2016)



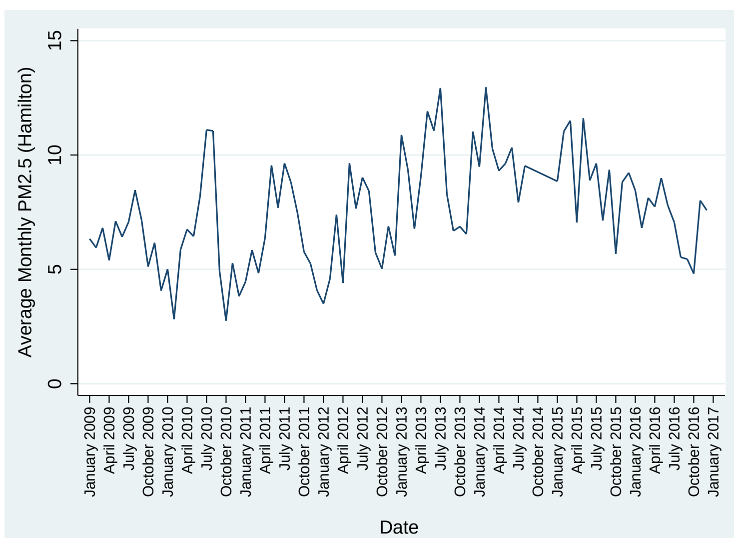
Source: Author's own calculations.

Figure 3.5: Average Monthly O_3 in Hamilton (2009-2016)



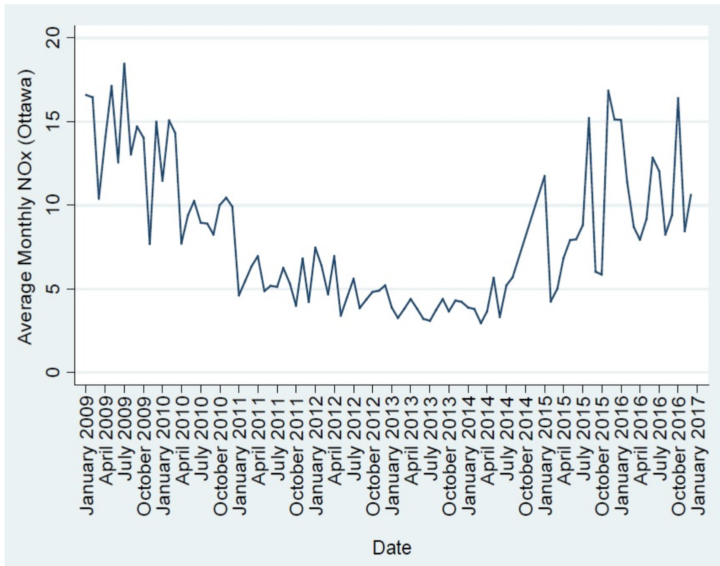
Source: Author's own calculations.

Figure 3.6: Average Monthly $PM_{2.5}$ in Hamilton (2009-2016)



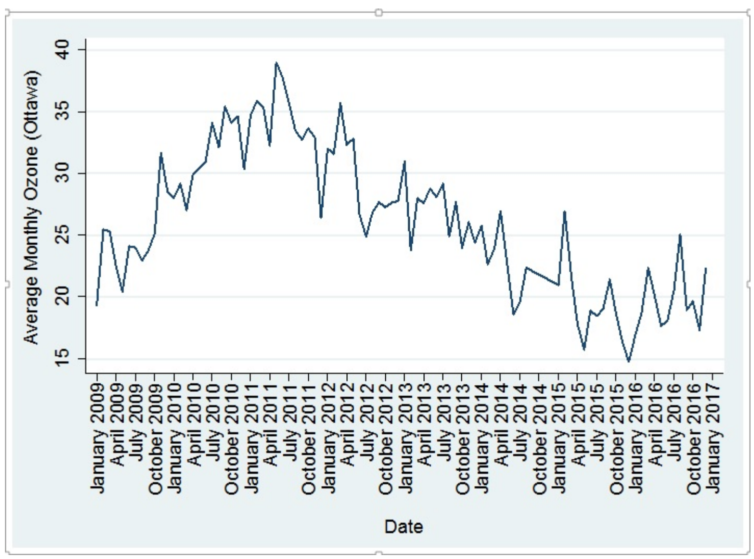
Source: Author's own calculations.

Figure 3.7: Average Monthly NO_x in Ottawa (2009-2016)



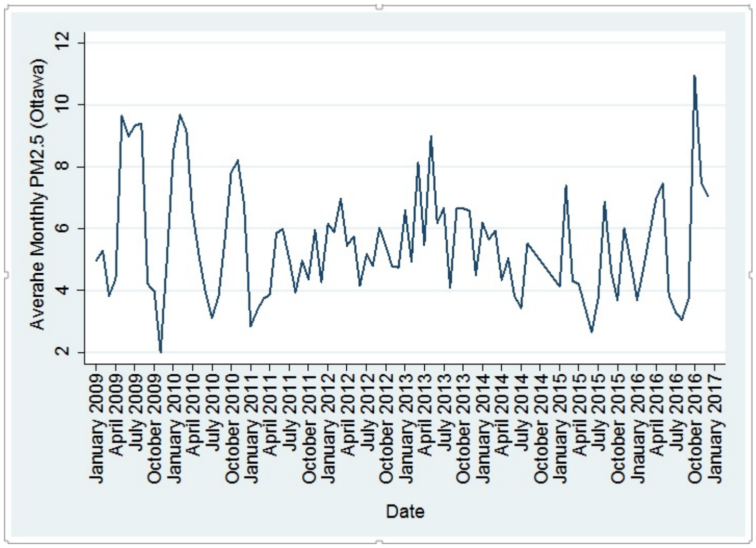
Source: Author's own calculations.

Figure 3.8: Average Monthly O_3 in Ottawa (2009-2016)



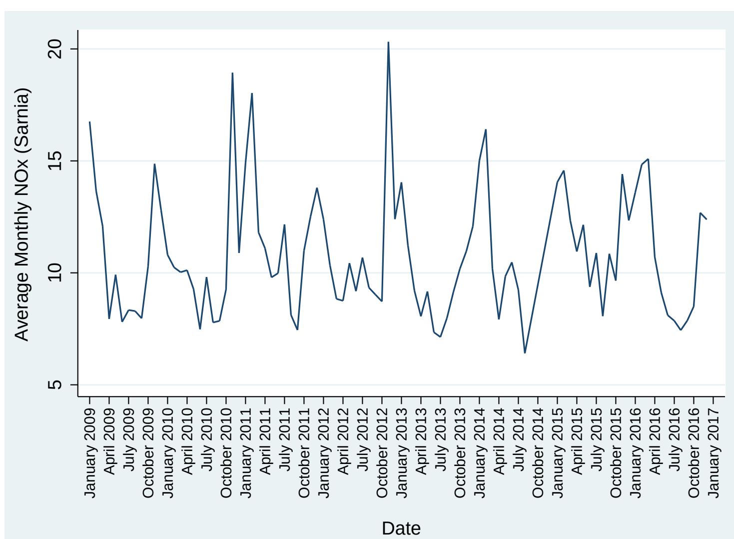
Source: Author's own calculations.

Figure 3.9: Average Monthly $PM_{2.5}$ in Ottawa (2009-2016)



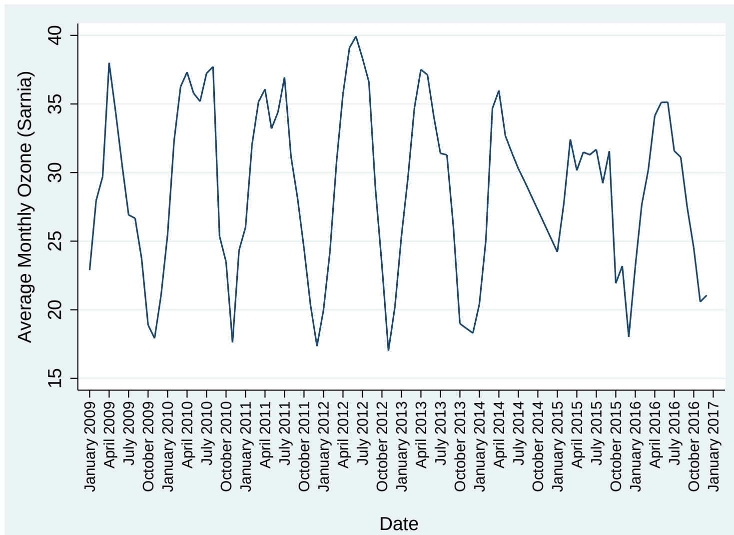
Source: Author's own calculations.

Figure 3.10: Average Monthly NO_x in Sarnia (2009-2016)



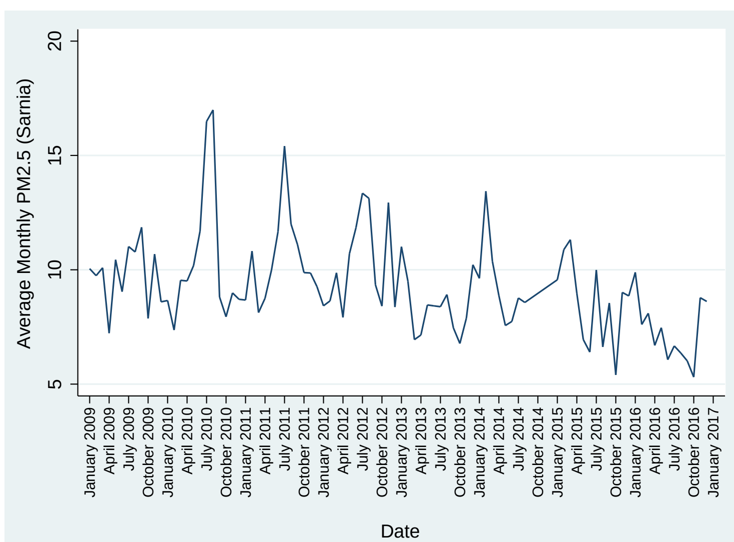
Source: Author's own calculations.

Figure 3.11: Average Monthly O_3 in Sarnia (2009-2016)



Source: Author's own calculations.

Figure 3.12: Average Monthly $PM_{2.5}$ in Sarnia (2009-2016)



Source: Author's own calculations.

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Appendix A

Appendices of Chapter 1

Figure A.1: Map of the Tri-Cities including CTs and DAs within boundaries of each.

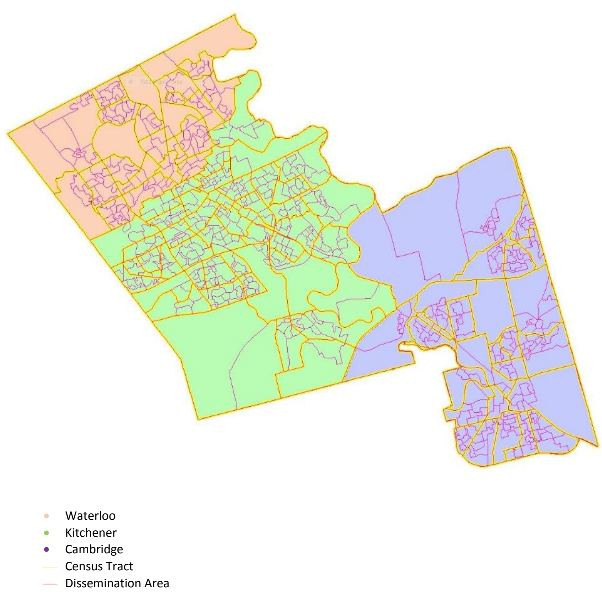


Figure A.2: Distribution of houses in the Tri-Cities, CTs and DAs.

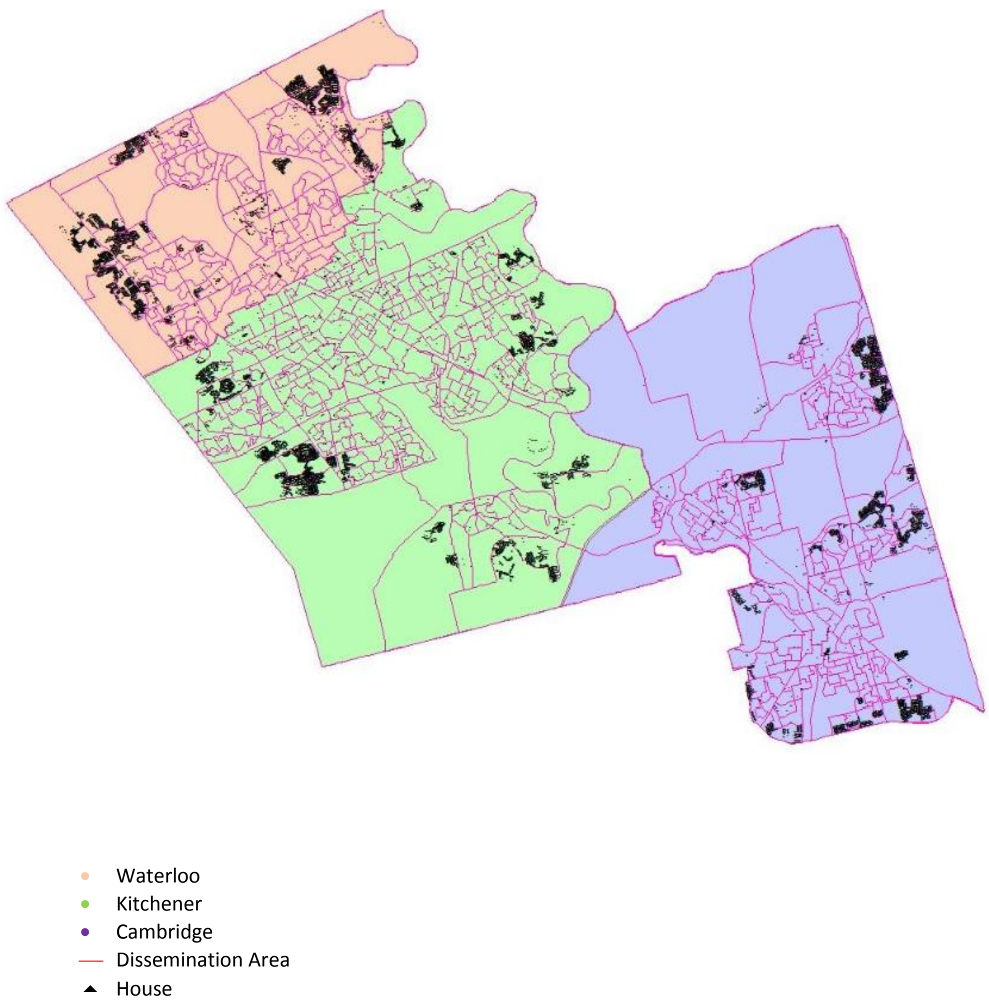


Figure A.3: Distribution of houses in CTs and DAs of Cambridge.

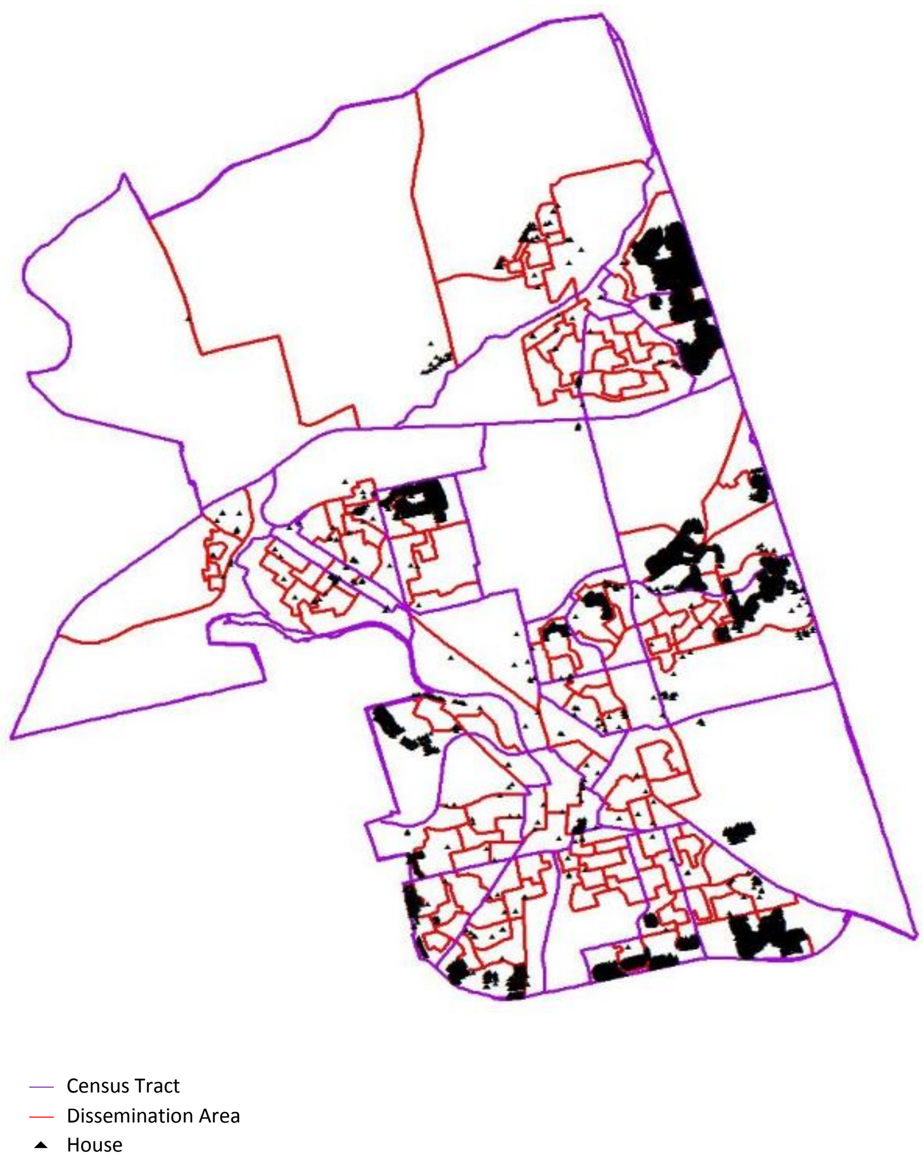


Figure A.4: Distribution of houses in CTs and DAs of Kitchener.

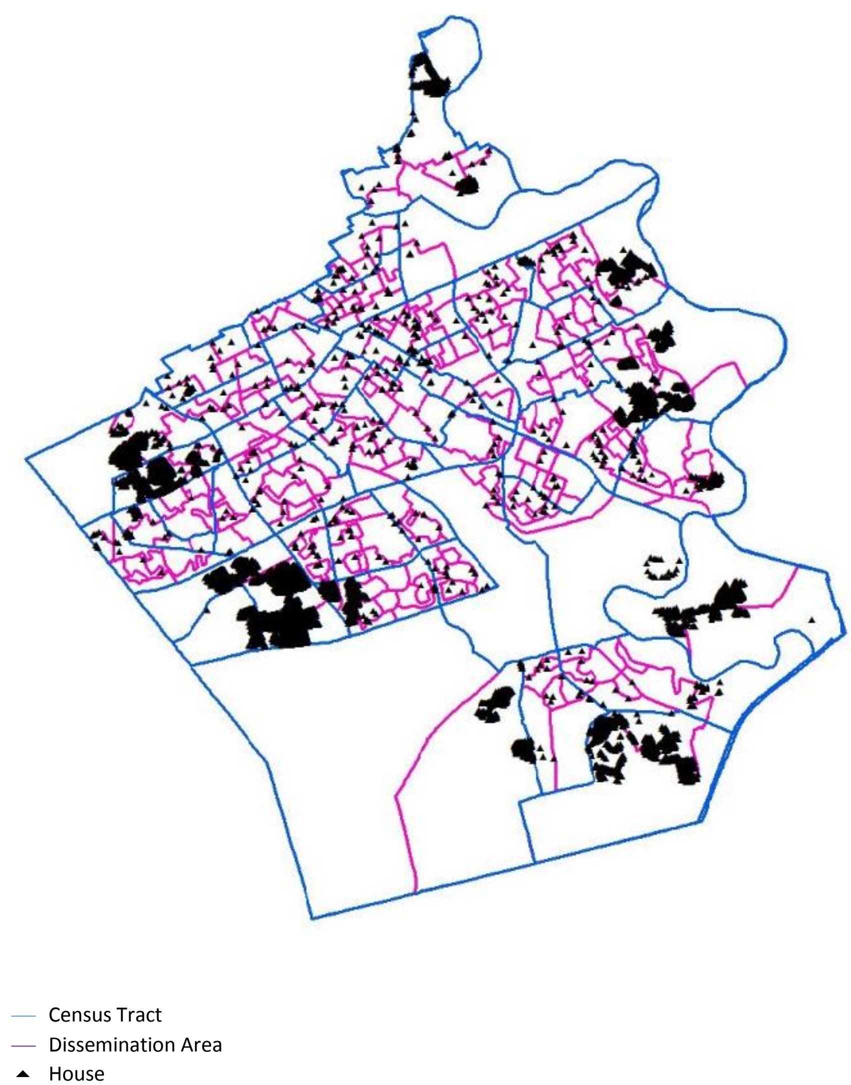
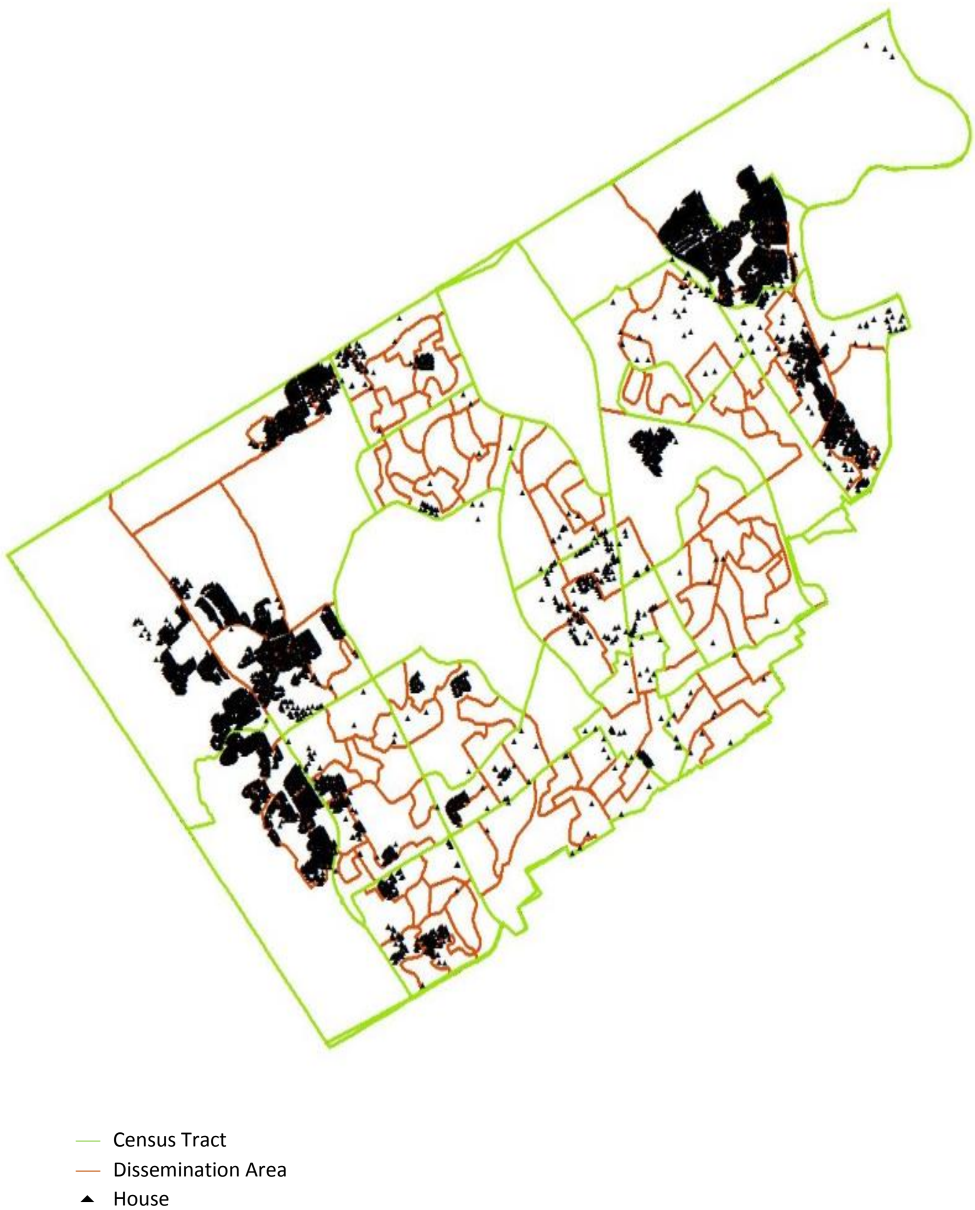


Figure A.5: Distribution of houses in CTs and DAs of Waterloo.



Appendix B

Appendices of Chapter 2

Table B.1: Studies on the impact of smart-metering on household electricity consumption

Author	Data	Term	Dep. Var	Ind. Var	Method	Main Findings	Critique
McCoy and Lyons [2014]	CER	2010	1.Binary adopter 2.Count of in trial adoption	Adoption of energy efficient measures	1.Logit 2.Neg. binomial	HH decresead electricity consumption as informed about TOU tarrifs & usages.	Short time-scale
Gilbert and Zivin [2014]	1.SGDE&E 2.Weather station in Escondid	2009-2010	Daily electricity consumption	1.CDH 2.HDH 3.HH specific temperature responses	OLS	HHs reduces energy consumption by 6% to 1% in a week after receiving the bills.	Short time-scale
Jack et al. [2015]	Admin. records of Cape-town	2012	electrivity Purchasing Pattern	1.Property Value 2.Month fixed effects 3. year fixed effects	OLS	Pre-paid electricity meters adds flexibility in how & when poor HHs purchase electricity.	Electricity purchase pattern rather than electricity consumption pattern is observed.
Kavousian et al. [2013]	10-min interval smart meter data for 1628 HHs	2010	Min, max and range electricity consumption	1. House size 2. House age 3. Type of building 4.CDD 5.HDD 6.Various consumption appliances	WLS	Weather & physcal characteristics are most important determinants of electricity consumption.	1. Short time_scale 2.Targeted specific HH whose income are over $150,000.00

Table B.2: Studies on the impact of sub-metering in multi-unit residential buildings

Author	Data	Term	Dep. Var	Ind. Var	Method	Main Findings	Critique
Dewees and Tombe [2011]	1. Environ. canada 2. Sample condo building in Toronto	2001-2010	Log of electricity consumption	1. HDD 2. CDD 3. Sub-met. dummy	OLS	1.Sub_metering reduces electricity usage by 15% to 25% in the selected apt. 2.Social net benefit depends on factors such as design of apt. & value assigned to externalities from generators.	1.Relied on short-time sub-met. data 2.Selected sample is small.
Munley et al. [1990]	Controlled experiment of a large garden apt. in Wash.	1978-1980	Box-cox trans. on HH electricity consumption	1. HH income 2.Number of children under 18 3. Number of KWH consumed 4.Top floor apt. 5.CD &HD 6.Lagged price of electricity	MLE GLS	if installing sub-metering cost is ignored, sub-metering is profitable and provides non-negligable net gain in welfare.	1.Short time-scale 2.Generator externality is ignored in welfare analysis.

Table B.3: Dickey-Fuller Test for Unit Root in Natural Log of HOEP

Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
-7.813	-3.96	-3.41	-3.12

P-value = 0.0000

Note: Test is performed on the Log of HOEP data for the period from January 2009 to August 2014.

Appendix C

Appendices of Chapter 3

Table C.1: Dickey-Fuller Test for Unit Root in NO_x Pollution in Toronto

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-77.92	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the NO_x data of Toronto for the period from January 2009 to December 2016.

Table C.2: Dickey-Fuller Test for Unit Root in O_3 Pollution in Toronto

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-57.526	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the O_3 data of Toronto for the period from January 2009 to December 2016.

Table C.3: Dickey-Fuller Test for Unit Root in $PM_{2.5}$ Pollution in Toronto

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-67.182	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the $PM_{2.5}$ data of Toronto for the period from January 2009 to December 2016.

Table C.4: Dickey-Fuller Test for Unit Root in NO_x Pollution in Hamilton

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-78.147	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the NO_x data of Hamilton for the period from January 2009 to December 2016.

Table C.5: Dickey-Fuller Test for Unit Root in O_3 Pollution in Hamilton

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-55.456	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the O_3 data of Hamilton for the period from January 2009 to December 2016.

Table C.6: Dickey-Fuller Test for Unit Root in $PM_{2.5}$ Pollution in Hamilton

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-72.121	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the $PM_{2.5}$ data of Hamilton for the period from January 2009 to December 2016.

Table C.7: Dickey-Fuller Test for Unit Root in NO_x Pollution in Sarnia

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-89.514	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the NO_x data of Sarnia for the period from January 2009 to December 2016.

Table C.8: Dickey-Fuller Test for Unit Root in O_3 Pollution in Sarnia

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-70.22	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the O_3 data of Sarnia for the period from January 2009 to December 2016.

Table C.9: Dickey-Fuller Test for Unit Root in $PM_{2.5}$ Pollution in Sarnia

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
-57.306	-3.43	-2.86	-2.57

p-value for Z(t) = 0.0000

Note: Test is performed on the $PM_{2.5}$ data of Sarnia for the period from January 2009 to December 2016.