Effects of Climate Change on Industrial Demand for Electricity in New Brunswick

by

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Abstract

Climate change is a pervasive and intricate issue with irreversible long-term consequences. New Brunswick faces escalating hot days, storms, and sea levels, impacting electricity usage. This study addresses the previously unexplored impact of climate change on industrial electricity demand from 1970 to 2022, acknowledging its significance in bridging knowledge gaps.

The study employs a production function to derive industrial demand for electricity. Consequently, six econometric models, estimated through Ordinary Least Squares, reveal a direct link between temperature and demand: a 1°C rise corresponds to a 0.0025 Petajoules increase. There is also an inverse relationship between electricity price and industrial demand and higher economic activity increases industrial demand as well.

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List of Abbreviations

GDP: Gross Domestic Product

SSM: State-Space Model

CES: Constant Elasticity of Substitution

CGE: Computable general equilibrium

SEM: Simultaneous Equation Model

SUR: Seemingly Unrelated Regressions

ADF: Augmented Dickey-Fuller

ARDL: Autoregressive Distributed Lag

GCM: General Circulation Model

HDD: Heating Degree Days

CDD: Cooling Degree Days

WTP: willingness-to-pay

IED: Industrial Electricity Demand

IEP: Industrial Electricity Price

LI: Labour Income

VCAsset: Value of Capital Asset

VAdded: Value Added of Industry

TVP: time-varying parameter

TSP: Trend-Stationary Process

DSP: difference-stationary process

IV: Instrumental Variable

2SLS: two-stage least squares

OLS: Ordinary Least Squares

Chapter 1: Introduction

Climate change is becoming a growing public and political concern. The majority of climate scientists agree that climate change is occurring and that most of it is caused by human activity. The main observable features of climate change in New Brunswick include: increases in the number of hot days, precipitations, storm severity, as well as sea level rise that will have an impact on all aspects of New Brunswick's environment, economy, and society.

The effects of climate change are already being felt in the province. Over the last 30 years, the average yearly temperature in New Brunswick has risen by 1.1°C. This increase in temperature has led to rising sea levels, which have in turn increased the risk of flooding and coastal erosion. In the past, extreme weather events have caused significant damage in the province. Since December 2016, several of these events have occurred, including snow- and freezing rainstorms that caused prolonged power outages and destruction of electrical infrastructure in the Acadian Peninsula.

In 2018 and 2019, there were back-to-back spring floods along the St. John River, which set records for flooding and caused the most damage of any flood event in the province. Furthermore, in the late summer of 2019, post-tropical storm Dorian brought high winds and heavy rain that resulted in extensive damage to property, infrastructure, and shorelines (GNB, 2018).

As temperatures drop or rise during the year, the demand for electricity increases, since the usage of electric heating systems or air conditioners increase. For example, heating systems accounts for about half of the monthly energy bill for many homes in New Brunswick when the temperatures drop.

Figure 1.1 shows that during a chilly January day, the peak demand for energy could soar up to 3,000 Megawatts, which is significantly higher than the demand during a summer morning when the usage is just half of that. This fluctuation in demand clearly illustrates the impact of temperature on energy system (Energy NB Power). So, changes in temperature can have a significant impact on the overall electricity demand.

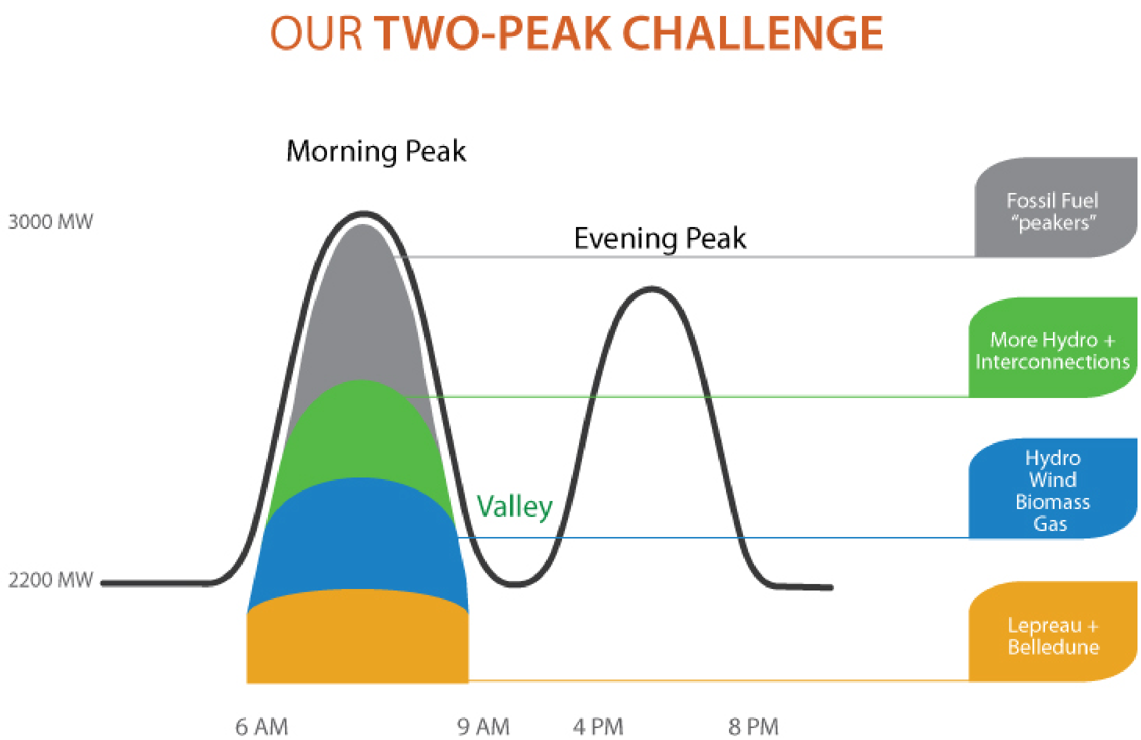

Figure 1.1. Peak electricity times in NB

Moreover, the debate over the Trans Mountain pipeline expansion in Canada is an excellent example of why climate change mitigation remains difficult. On the one hand, supporters of the project have argued that it will have significant economic benefits due to the creation of new jobs and lower production costs. Opponents of the project have claimed, among other things, that it will prevent Canada from meeting its 2030 emission target. This argument is based on the widely held belief that the relationship between energy consumption and climate change is one-way. That is, energy production and consumption directly contribute to global warming. While this is correct, it ignores the feedback effects of changes in weather patterns on energy supply and demand.

In the case of electricity, burning fossil fuels is necessary for the generation process, which increases the atmospheric concentrations of greenhouse gases. The demand for electricity also varies as a result of changes in the weather, particularly changes in temperature. Sometimes a rise in temperature can actually reduce demand since less heating is needed. Given the two-way interaction between both, disregarding how climate change is affecting electricity demand could result in ineffective mitigation strategies.

Nearly all studies that discuss the relationship between electricity use and climate change highlight the importance of temperature on electricity demand. Globally, the effects of climate change vary greatly depending on the region's geography, politics, and economy. So, changes in the Earth's climatic system over the next few decades may have significant direct and indirect effects on electricity demand in many regions (IPCC, 2013). Moreover, the gradual rise in surface temperatures is referred to as global warming. This rise alters energy consumption due to variations in cooling and heating demand (Clarke et al., 2018).

This study seeks to address the main question: how could climate change have impacted industrial demand for electricity during 1970-2022?. This study attempts to answer this question by estimating the relationship between energy consumption and climate change in the province using time series analysis.

The paper is organized as follows: Section 2 discusses theory, and econometrics methods, found in recent literature associated with the relationship between electricity consumption and climate change. Section 3 explains the methodology used in this study to estimate the impacts of climate change on industrial electricity demand. Section 4 describes data and presents detailed results of our model estimation. Section 5 concludes with some policy implications. Finally, Section 6 discusses lessons and future work with the existing content.

Chapter 2: Literature review

2.1. Theoretical background

In the literature, there are four theoretical approaches for deriving industrial energy demand, namely Aggregate Production Function method, General Equilibrium, Partial Equilibrium, and Ad hoc or Econometric Methods.

2.1.1. Aggregate Production Function Method

Production functions are designed to explain economic output as a function of factors of production. They are central to macroeconomic and microeconomic modelling, growth accounting, and the comparison of empirical research with economic theory (Brockway et al., 2017). In an aggregate production function, all factors of production such as capital, natural resources, and technology except for the employed labour are fixed, and the aggregate production function explains the total output of the economy by the total amount of labour employed in the economy. If an economy operates on its aggregate production function, it is producing its potential level of output (Saylor Academy, n.d.). Cobb–Douglas (C-D) and Constant Elasticity of Substitution (CES) functions are the two most common aggregate production functions (Duffy & Papageorgiou 2000; Felipe & Adams 2005).

Recently, adding energy as a factor of production in aggregate production functions has regained popularity (van der Werf, 2008). There are two possible reasons for this renewed interest.; First, there is growing evidence that tightly links economic growth is strongly linked to energy. Second, the effects of energy in an energy–economic model cannot be studied unless it is included as an endogenous factor of production (Stern n.d.; Kalimeris et al. 2014).

In this report, our main target is the industrial electricity demand. In order to produce any commodity, it is necessary to have factors (or inputs) of production. In general, there are four basic factors of production such as labour, physical capital, land, and entrepreneurship. Since energy is an important factor of production, let us consider the following production function:

$$Q = F(K, L, E) \tag{2.1}$$

where Q is output, K is quantity of capital, L is quantity of labour, E is quantity of energy and F shows the production process or technology that transforms inputs to output. The underlying assumption of a producer's behavior is profit maximization. The difference between total revenue and total cost of production is gross profit. Total revenue is:

$$TR = P \times Q \tag{2.2}$$

And total cost of production is the sum of expenditures:

$$TC = P_L L + P_K K + P_E E \tag{2.3}$$

Profit maximization problem can be written as follows:

$$\max\ [\, PQ - (P_L L + P_K K + P_E E)] \tag{2.4}$$

S.t.

$$Q = F(K, L, E)$$

Where F depicts the process of production or the technology that converts inputs into outputs.

Equation (2.4) has the potential to be represented using the production function of the Cobb-Douglas form. This representation involves disregarding terms of higher order (refer to Nordhaus, 1975, 1977).

$$Q = AK^{\alpha}L^{\beta}E^{\gamma}A^{\eta} \tag{2.5}$$

Where α, β, γ, and η denote the elasticities of production in relation to labor, capital, energy, and climatic variable respectively.

Solution to this problem is a set of factor demand functions. Subsequently, the energy demand equation below can be deduced from Equation (2.5) as follows:

$$e = a_0 + a_1 P_L + a_2 P_K + a_3 P_E + a_4 P_a + a_5 V \tag{2.6}$$

The small letters represent the natural logarithm representations of the related variables in Equation (2.6) and the detailed explanation for the mathematical derivation can be found in the methodology and Appendix.

2.1.2. General Equilibrium

Computable general equilibrium (CGE) models developed by (Jorgenson 1984; McKibbin and Wilcoxen 1998; McKitrick 1998; Fisher-Vanden and Ho 2007). CGE models are simulations that combine realistic economic data with the abstract general equilibrium structure formalized by Arrow and Debreu model to solve numerically for the levels of supply, demand and price that support equilibrium across a specified set of markets. CGE models have emerged as a standard pseudo-empirical tool for policy evaluation (Wing, n.d.). These models are also utilized to analyze resource allocation and income distribution issues in market economies (Bergman, 2005).

A solid microeconomic foundation is the most important strength of the CGE model (Jorgenson, 1984). However, the results of CGE models are highly dependent on key economic parameters on which uncertainties remain and are complex to implement. In addition, those models are time-consuming and expensive (Bergman, 2005). Therefore, it is very difficult to specify and calibrate a fully forward-looking CGE model in the complementarity format of equilibrium (Wing, 2009).

In CGE models, different sectors of the economy including energy sector can be modelled explicitly to derive the required demand function. To use CGE models, first we need to find the functional forms for different economic relationships, such as utility function of households or production function of producers. Second, we need to model energy sector which requires a lot of preliminary empirical work, econometric analysis to derive the demand for electricity.

2.1.3. Partial Equilibrium

A partial equilibrium analysis either assumes that the sector in question is very small and therefore has little, if any, impact on other sectors of the economy or ignores effects on other industries in the economy altogether (Saylor Academy, 2012).

Partial equilibrium analysis is especially suited for two types of analyses. First, it can be used to analyze the immediate or primary effects of economic disturbance of any type. Second, it can be used to answer questions associated with economic impacts on a specific industry or a sector of an economy and which do not produce any disturbances to the rest of the economy.

There are several limitations of partial equilibrium analysis. Firstly, it assumes that an economic disturbance in a particular industry has only local effects, which rarely happens in real life. Secondly, partial equilibrium gives us a simpler framework with many restrictive assumptions. In Marshall’s view, the best we can do is to examine a commodity from the viewpoint of variables such as price, cost, and quantity. As such, we cannot easily examine every aspect and every repercussion. Therefore, it is applied mainly to the analysis of the equilibrium of a consumer, a firm, and an industry (Pal, 2022).

2.1.4. Ad hoc or Econometrics Methods

Ad-hoc analysis is a technical term that refers to a powerful method for obtaining precise answers to specific business inquiries. Its purpose is to provide comprehensive insights into the data mining process. As a result, data mining outsourcing companies greatly benefit from harnessing the potential of this analytical technique.

Also, data digging involves thoroughly examining a large amount of information to discover patterns and connections present in the past and ongoing operations of a business. Data digging, known as data mining or data exploration, refers to the process of extracting valuable insights and patterns from large volumes of data.

It involves using various techniques and tools to discover hidden relationships, trends, and patterns within the data, which can then be used to inform decision-making, improve processes, and gain a competitive advantage (Han et al., 2012). Data digging typically involves several steps: data collection, data cleaning and preparation, data exploration, data mining techniques, pattern identification and analysis, and interpretation and reporting (Han et al., 2012).

Econometrics means “economic measurement” (Quliaris, 2011). Measurement is a vital part of econometrics, but the scope of econometrics is much broader. Econometrics uses economic theory, mathematics, and statistical inference to quantify economic phenomena. In other words, it turns theoretical economic models into useful tools for economic policymaking (Quliaris, 2011). Giving empirical content to economic theory and subjecting economic theory to potentially falsifying tests are two important objectives of econometric models (Raihan, 2021). Also, there are eight stages in the process of developing econometric models, including: Statement of theory/hypothesis, specification of the mathematical model, specification of the econometric model, obtaining the data / conducting preliminary data analysis, estimation of the econometric model and interpretation of regression results, diagnostic analysis, hypothesis testing, and prediction/forecasting (Raihan, 2021).

Econometric models aim to measure the connection between the variable being predicted (known as the output variable) and various factors that impact it. These factors are often called explanatory variables or drivers, as they help explain changes in the output variable.

Moreover, econometric forecasting provides notable advantages for making informed predictions. Firstly, it holds the promise of enhanced accuracy, enabling more reliable projections. Secondly, it empowers analysts to explore the impact of various scenarios, encompassing both optimistic and pessimistic possibilities. This versatility enables a comprehensive evaluation of potential outcomes. Lastly, econometric forecasting facilitates a deeper understanding of the key factors influencing forecast uncertainty, allowing for more insightful decision-making. Overall, these advantages make econometric forecasting an indispensable tool for gaining valuable insights and making informed decisions in a dynamic and uncertain economic landscape (Simpson and Gotham, 2014).

In this study, we chose the production function method. The reason for our choice is obvious: The production function is used to derive a standard energy demand equation as factor demand, in which the energy price and income are the explanatory variables. Uri (1982) Beenstock & Dalziel (1986) have applied production function to derive energy demand. Nevertheless, Hankinson and Rhys (1983) and Bhattacharyy and Timilsina (2009) explained that standard energy demand depend on the research question.

2.2. Econometrics Models

According to the literature, basically there are two econometric methods that have been applied to estimate energy demand using the above-described chosen approach, namely Simultaneous Equations Method and Time Series analysis. After deriving the production function, a time series analysis is adopted in this report.

A Simultaneous Equation Model (SEM) is a model in the form of a set of linear simultaneous equations. While standard regression analysis uses a single equation model, SEM models contain two or more equations (Glen, 2021). For more detail see, (IIT Kanpur 2021; Henningsen and Hamann 2015).

The Seemingly Unrelated Regressions (SUR) model can be further generalized into the Simultaneous Equation Model, where the right-hand side regressors can also be endogenous variables. Arnold Zellner (1962) proposed the seemingly unrelated regressions or seemingly unrelated regression equations model in 1962. It is a generalization of a linear regression model made up of multiple regression equations, each with its own dependent variable and potentially different sets of exogenous explanatory variables. Using standard ordinary least squares, the model can be estimated equation by equation. Such estimates are consistent, but not as efficient as in the SUR model, which is essentially feasible for generalized least squares with a specific form of the variance-covariance matrix (Srivastava and Giles 1987; Srivastava and Dwivedi 1979; Green 2012).

Simultaneous equations refer to models that involve multiple response variables, and their solutions are determined through a balance between conflicting forces. In terms of econometrics, these equations present a problem similar to endogenous variables. This similarity arises from the fact that the interplay between dependent variables can be seen as a form of endogeneity. A classic illustration of an economic simultaneous equation problem is the supply and demand model, where the interdependence between price and quantity is determined by the interplay of supply and demand factors (Colonescu, 2016).

We chose time-series analysis because these models use economic theory as a guide to variable selection and rely on past patterns in the data to predict the future. In fact, time-series analysis typically forecasts the future by implicitly extrapolating past policies. Good forecasting performance, plus the relatively low cost of developing and maintaining time-series forecasting models, make time-series modelling an attractive way to produce baseline economic forecasts (Witson, in proceeding).

Time series data assumes that the underlying time series is stationary. Stationary data refers to the time series with constant mean and variance over time. The data is considered non-stationary if there is a strong trend or seasonality observed.

Technically, in time series econometrics, a time series that has a unit root is called a non-stationary process. Dickey and Fuller (1979) developed a procedure for testing whether a time series has a unit root. The Augmented Dickey-Fuller (ADF) test is the most commonly used test to detect the presence of a unit root.

There is the so-called state space model (SSM) which is also a time series model. The term emerged in the 1960s in the field of control engineering. The advantage of using SSM is that they have become a continuously important instruments for research in finance and economics in recent years (Hamilton, 1994). SSM is a robust method for capturing consumers' dynamic behavior with time-varying characteristics (Nagbe et al., 2018). One of the main advantages of SSM is estimation of a model with time-varying parameters based on the Kalman filter. SSM not only considers the unobserved variable such as economic activity, the regulation of prices, structural changes but it can also demonstrate price and income elasticity over time (Tong and Yang 2011; Arisoy and Ozturk 2014).

2.3. Industrial Demand for Electricity: Microeconomic Variables

Many researchers have studied industrial electricity demand in various countries. Beenstock et al (1999) evaluate electricity demand in the household and industry sectors in Israel. They used dynamic regression and cointegration techniques and found that the long-run elasticities of industrial sector are 0.99 to 1.12 with regard to economic activity and –0.31 to –0.44 with regard to electricity price.

Kamerschen & Porter (2004) used a partial-adjustment and a simultaneous equation approach to estimate US residential, industrial, and total electricity demand. This study shows that simultaneous models provide negative price elasticity estimates for the residential, industrial and total electricity samples. They recommend that residential clients are more price sensitive than industrial clients. Also, it appears that weather conditions have a significant influence on the residential sector, with cold weather having a greater impact on demand compared to hot weather.

Cialani & Mortazavi (2018) used a dynamic partial adjustment model to estimate price elasticities, and effects of other variables on electricity consumption by using GMM (generalized method of moments) and ML (maximum likelihood) approaches. They found that the residential sector is less sensitive to price fluctuations in the short and long run than the industrial sector. Also, unless the increase is significant, a rise in electricity prices will have little impact on residential and industrial electricity consumption.

Khan & Abbas (2016) examined the aggregate and sectoral dynamics of electricity demand in Pakistan from 1978 to 2012. They concluded that at both the total and disaggregate stages, changes in income are more sensitive to price fluctuations. Arisoy & Ozturk (2014) showed that electricity is a necessity, and price increases have little impact on consumer behaviour.

Polemis (2007) analyzed aggregate oil and electricity demand functions for the Greek industry and used a multivariate cointegration technique. He showed that long-run elasticities are equal to 0.85 and –0.85 with respect to economic activity and price, while in the short-run they are 0.61 and –0.35, respectively.

Table 2.1 summarizes recent studies in which industrial electricity demand is considered according to econometric method used, model specification, country, period covered, and data frequency.

Table 2.1. Main features and key findings of previous studies

Authors	Country	Model	Study period	Key outputs
Beenstock et al (1999)	Israel	dynamic regression and cointegration techniques	1973-1994	The long-run elasticities of industrial sector are 0.99 to 1.12 regarding economic activity and –0.31 to –0.44 regarding electricity price.
Polemis (2007)	Greece	Cointegration	1970–2004	The long-run elasticities are 0.85 and –0.85 regarding economic activity and price, while in the short-run they amount to 0.61 and –0.35, respectively.
Kamerschen, and Porter (2004)	US	partial-adjustment and a	1973–1998	Residential clients are more price sensitive than industrial clients. Although Flow adjustment models produce positive price elasticity estimates

		simultaneous equation approach		in some cases and sectoral weather sensitivity impact of cold weather on demand is more than hot weather.
Arshad Khan and Abbas (2016)	Pakistan	Panel cointegration test and Fully Modified Ordinary Least Squares method	1978–2012	both the total and disaggregate stages, the changes in income are more sensitive to price fluctuations.
Arisoy and Ozturk (2014)	Turkey	State-space model	1960 - 2008	electricity is a necessary commodity, and price increases have little impact on consumer behavior.
Cialani and Mortazavi – (2018)	29 European countries	GMM (generalized method of moments) and ML (maximum likelihood) approaches	1995–2015	The residential sector is less sensitive to price fluctuations in the short and long run than the industrial sector. Also, unless the increase is significant, a rise in electricity prices will have little impact on residential and industrial electricity consumption
Dilaver and Hunt (2011)	Turkey	Structural Time Series Model	1960-2008	They focused on the relationship between Turkish industrial electricity consumption, industrial value added, and electricity prices that predict Turkey's industrial electricity.

After an extensive review, it becomes evident that two significant factors, namely price and value added, hold paramount importance as fundamental microeconomic determinants that shape industrial electricity demand. This conclusion is supported by the comprehensive study conducted by Dilaver Zafer and Hunt (2011) focusing on the Turkish context. Their research delved into the intricate relationship between Turkish industrial electricity consumption, industrial value added, and electricity prices, highlighting the pivotal role these factors play in influencing the overall demand for electricity in Turkey's industrial sector.

2.4. Relationship Between Climate Change and Industrial Demand for Electricity

There have been several studies examining the impact of climate change on electricity demand. Sailor (2001) used uniform climate perturbations and actual General Circulation Model (GCM) to estimate potential changes in electricity consumption as a consequence of climate change. This study found a wide range of electricity demand effects: one state experiencing decreased loads due to climate change and the others experiencing significant increases in annual per capita residential and commercial electricity consumption.

Ahmed et. al (2012) examined the impact of climate change on the electricity demand in New South Wales, Australia. They concluded that electricity demands in summer and spring will increase due to climate change.

Parkpoom and Harrison (2008) showed how climate change will impact Thailand's daily, seasonal, and long-term electricity demand. This study indicated that mean annual temperatures in Thailand will increase by 1.74 to 3.43 C by 2080, including rises in Thai peak electricity demand of 1.5%–3.1% in the 2020s, 3.7% 8.3% in the 2050s, and 6.6%–15.3% in the 2080s. Trotter et. al (2016) analyzed three climate change scenarios and indicated that there is significant weather uncertainty in all scenarios, with up to 400 TWh separating the 10th and the 90th percentiles, or approximately ±17% relative to the mean.

Eskeland and Mideksa (2010) used a panel data set of 31 countries to study the relationship between European electricity consumption and outdoor temperature and other variables. They found that the demand for heating and cooling is different since the demand for heating will decrease in Northern Europe while the demand for cooling will increase in Southern Europe.

Fan et al. (2019) discovered that the heating degree days (HDD) and cooling degree days (CDD) have a positive impact on the per capita electricity demand. In addition, it was found that total variations in electricity demand caused by climatic factors by 2100 under the different scenarios and the impact of climate warming on China's electricity demand are significant.

Franco and Sanstad (2008) investigated climate change and its potential effect on California's electric power system. They utilized recent data to estimate the impact of temperature changes on electricity consumption and peak demand across different locations in California. By combining these findings with new projections of regional climate change, the study provides estimates of the potential impacts of future temperature changes on electricity consumption, peak demand, and associated economic costs. The authors also outlined current and prospective strategies and identified key areas for future research to better inform policymakers and industry stakeholders.

Demand for electricity exhibits a consistent pattern of seasonality, which is attributed to the nonlinear connection between demand and temperature fluctuations. Changes in industrial electricity demand predominantly stem from adjustments in heating and cooling needs in response to temperature variations. When the weather is extremely cold, a rise in temperature initially leads to a decrease in electricity demand as heating requirements decline. However, as the temperature continues to increase, the demand for electricity for cooling purposes rises. Theoretically, this creates a U-shaped relationship between the quantity of electricity demanded and temperature.

For example, Sliva et. al (2020) indicated that the relationship between temperature and electricity consumption is U-shaped and the significance of taking into account country specificities in the analysis and comparing several model specifications For more details refer to (Ruth and Lin 2006; Deschênes and Greenstone 2007; Franco and Sanstad 2007; Aroonruengsawat and Auffhammer 2011; Li et all 2018).

Despite the recent progress made in understanding how climate change affects electricity demand, there are still some areas of research that have not been fully explored or understood. To the best of our knowledge, this study represents the initial step to examine the influence of climate change, particularly global warming, on industrial electricity consumption in the province of New Brunswick. Yevdokimov et al. (2018) conducted a study to determine the willingness-to-pay (WTP) for electricity in New Brunswick from 1991 to 2013. While the study included environmental variables as a factor influencing WTP, the authors did not investigate the specific impact of climate variables.

Climate change has posed significant and ongoing challenges throughout the past century and continues to do so. It is crucial for the province of New Brunswick to have a comprehensive understanding of the relationship between global warming and industrial demand for electricity. Therefore, the primary objective of this report is to provide policymakers in New Brunswick with valuable insights into this issue. Also, the effect of climate change on industrial electricity demand in New Brunswick has remained unexplored in this group of studies and this paper closes this recognized research gap.

Chapter 3: Methodology

This section discusses first how energy demand specifications can be theoretically derived and then how it can be used to set up the econometric model to estimate industrial electricity demand. As mentioned previously, we derive factor demand for industrial electricity from production function. In a competitive market, profit maximization can be reduced to cost minimization. Therefore, we can derive factor demand for industrial electricity from the cost function as (Mikayilov and Hasanov, 2019).

We can define our production function as follows: Inputs are quantity of labour (L), quantity of capital (K), energy (E), and some climatic variable (A). Mathematically it means

$$Q = F(K, L, E, A) \tag{3.1}$$

Our production function can be expressed by the Cobb-Douglas specification (Cobb and Douglas, 1928). Cobb-Douglas production function is convenient multiplicative form since powers become elasticities which make a good link between theoretical approach and empirical approach. Mathematically it is

$$Q = AK^{\alpha}L^{\beta}E^{\gamma}A^{\eta} \tag{3.2}$$

The goal of a producer of some commodity is to minimize total costs, which means to define the quantities of K, L, E, and A that minimize the following total cost function:

$$C = P_k K + P_l L + P_e E + P_a A \tag{3.3}$$

In Equation (3.3), C is total cost and, P_k, P_l, P_e, and P_a are prices of capital, labour, energy, and climate variable, respectively.

The exercise can then be formulated as a constrained optimization problem by treating the total cost function as an objective function and the production function as a constraint:

$$Min\ Cost = P_k K + P_l L + P_e E + P_a A \tag{3.4}$$

Subject to:

$$Q = AK^{\alpha} L^{\beta} E^{\gamma} A^{\eta} \tag{3.5}$$

The Lagrange multipliers method is used for constrained optimization and if we apply Lagrange, the industrial energy demand equation will be as follow:

$$lnE = \alpha_0^{"} + \alpha^{"} lnP_k + \beta^{"} lnP_l + \gamma^{"} lnP_e + \eta^{"} lnP_a + \delta^{"} lnV \tag{3.6}$$

$\alpha_0^{"}$ includes constant term and error term and $\alpha^{"}$, $\beta^{"}$, $\gamma^{"}$, $\eta^{"}$, $\delta^{"}$, and $\theta^{"}$ are the elasticities to be estimated econometrically; P_k , P_l , P_e, P_v, P_a are the prices of capital, labor, energy, climatic variable, V is industrial value-added. In other words, P_l is wage and P_k is the cost of capital. Thus, Equation (3.6) is the derived industrial energy demand, which shows the industrial demand for energy as a function of the prices of factors of production (labor, capital, and energy) and price of climatic variable as well as the industrial value-added as industrial income.

Appendix A contains a detailed explanation of the mathematical derivation of Equation (3.6). It is worth noting that similar theoretical frameworks for energy demand, such as Equation (3.6), have been developed by (Nordhaus 1977; Beenstock and Dalziel 1986; Hasanov and Mikayilov 2020; Mikayilov and Hasanov 2018).

According to Equation (3.6), all variables are time series in econometric sense and therefore we will be applying time series analysis to estimate the model. However, these variables can be stationary or non-stationary time series. That is why each variable should be tested for unit root.

In section 2.4, it was explained that the primary significance of the connection between industrial electricity demand and temperature is that the correlation between temperature fluctuations and demand is not linear. As the temperature gradually decreases from a higher point, the level of comfort initially improves. However, as the temperature continues to drop, the comfort level decreases, resulting in an increased level of consumption.

Since degree day variables address nonlinearity without using higher order terms of average temperature, thus improving the model's accuracy. Sailor and Munoz (1997) concluded that for electricity demand derived variables performs better than "primitive" climatic variables.

Cooling and heating degree days are commonly described in a similar manner with respect to certain base temperature(s).

$$CDD = T - \mathrm{T}_{Cooling} \tag{3.7}$$

$$HDD = \mathrm{T}_{Heating} - T \tag{3.8}$$

Where T represents the average of minimum and maximum temperatures for that day and $\mathrm{T}_{\mathrm{Cooling}}$, $\mathrm{T}_{Heating}$ represent baseline temperatures.

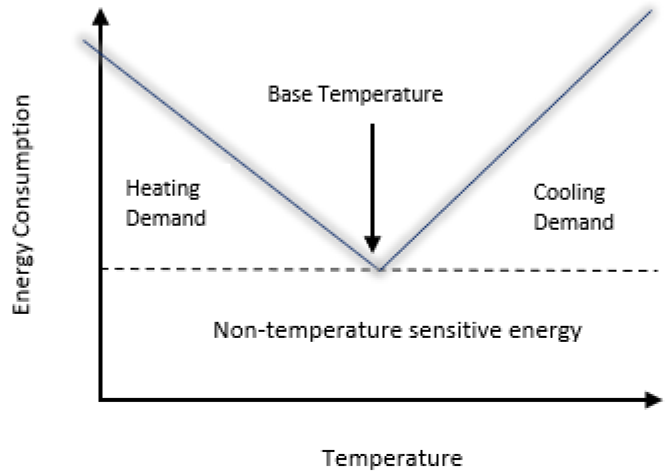

Figure 3.1. The relationship between temperature and energy consumption

The degree-day methodology, as illustrated in Figure 3.1 (Jager 1983; Amato et al. 2005; Hekkenberg et al. 2009), assumes a temperature–energy consumption relationship that resembles a V shape. When outdoor temperatures deviate from the base temperature, energy demand increases or decreases proportionally. In this study, we simplified the observed relationship between electricity consumption and temperature by using two linear functions in the V-shaped plot, employing a piecewise linear regression method. Additionally, a simple linear detrending technique was applied to eliminate any potential anthropogenic signal present in the observed residential and commercial electricity consumption data (Karoly et al., 2003).

It is expected that the importance and significance of $T_{Cooling}$ and $T_{Heating}$ can differ in different geographical areas. Also, numerous studies within this field of research employ the utilization of HDD and CDD as valuable metrics. These metrics indicate deviations from a specific threshold temperature that is typically associated with achieving optimal thermal comfort. For example, Hor et al. (2005) chose $T_{Cooling}$ and $T_{Heating}$ equal to 22°C when looking at the relationship between industrial electricity demand and weather variables in UK.

In the context of European countries, Eskeland and Mideksa (2010) defined the temperature thresholds as $\mathrm{T_{Cooling}}$= 22°C and $\mathrm{T}_{Heating}$= 18°C. Conversely, in North America, it is common to use a base temperature of 18°C for both cooling and heating, as suggested by (Nall and Arens 1979; de Dear and Brager 2001).

To address the lack of CDD and HDD projections specific to New Brunswick, we have adopted the conventional approach found in the existing literature for North America. We define the temperature thresholds for calculating CDD and HDD as $\mathrm{T}_{Cooling} = \mathrm{T}_{Heating}$= 18°C. This approach allows us to make meaningful comparisons and draw relevant insights based on established methodologies.

However, to provide more comprehensive information about the CDD and HDD variables used in our study, we will present detailed explanations in section 4. This section will delve into the specific calculations, definitions, and implications of CDD and HDD within the context of our research.

Chapter 4: Econometric Estimation and Results

4.1. Data for the Econometric Analysis

This section explains the data sources for this study and presents a summary of statistics of the data. Variables can be divided into different subgroups, such as microeconomic, industrial, and climatic variables.

Microeconomic variables

- Industrial Electricity Demand (IED): We use data from NB Power's System Information Archive to estimate the relationships between changes in climatic variables and industrial demand for electricity in New Brunswick. The raw data obtained represent the total demand for electricity in New Brunswick since NB Power's System Information Archive does not distinguish between residential and industrial demand. We use the annual dataset from Statistics Canada, which categories total electricity demand into four groups (residential, agriculture, mining and manufacturing and other industries) to obtain the relevant data.

- The price of electricity for industrial customers in the province of New Brunswick. In New Brunswick, electricity is priced progressively by blocks. As a result, we use average price which is obviously a simplification of reality.

- Value of capital assets: The value of the capital assets is spread over its useful life. The cost of capital method is used for this purpose. The cost of capital is the cost of a company's funds in economics and accounting, or the required rate of return on a portfolio company's existing securities from the perspective of an investor. Moreover, the cost of capital for a company is the sum of its debt (borrowed money) plus its equity (common and preferred share capital). Each component is weighted in order to express the cost as a percentage, which is referred to as the weighted average cost of capital (WACC).

- Labour Income: Labor Income consists of two components. The first component, known as Employee Compensation, encompasses the overall cost borne by employers for their wage and salary employees. It encompasses wages, salaries, all benefits (such as health and retirement benefits), and payroll taxes (including social security contributions, unemployment insurance taxes, etc.). This is commonly referred to as fully-loaded payroll. The second component of Labor Income is Proprietor Income (PI). PI refers to the earnings received by self-employed individuals and business owners who are not incorporated (Statistics Canada).

Industrial variables

- Industrial value-added: This can be calculated either as before or after deducting the consumption of fixed capital used in production. As a result, the value of an industry's gross value added is equal to its output of goods and services minus the value of its intermediate consumption of goods and services, and the value of its net value added is equal to the output less the values of both intermediate consumption and consumption of fixed capital (Kishori, 2000). It is expected that the industrial value added can have positive impacts on industrial electricity demand.

Climatic variables

- Monthly Temperature: We can use average temperatures during different periods of time, for example summer versus winter. Also, the difference between the average temperature (the annual average air temperature was constructed by using Environment and Natural Resources of Canada)[1] and a pre-set base temperature is referred to as cooling degree days (CDD) and heating degree days (HDD). In order to determine the daily CDD and HDD, we first gather information on the daily average temperature from Environment and Climate Change Canada's Climate dataset.
- CDD /HDD: Cooling degree days (CDDs) provide an estimate of the extent of cooling, such as air conditioning, needed to maintain a comfortable environment in a building during warmer periods. When the average daily temperature exceeds a certain threshold, CDDs start accumulating (refer to Degree Days Above). In Canada, the commonly used threshold temperature is 18°C. Higher CDD values suggest a higher demand for air conditioning.

[1] (http://climate.weather.gc.ca/historical_data/search_historic_data_e.html)

Heating degree days (HDDs) provide an estimate of the heating requirements in a building during colder months. They indicate the amount of heating, such as from a gas boiler, furnace, electric baseboard heaters, or fireplace, needed to maintain a comfortable indoor environment. HDDs are accumulated when the average daily temperature falls below a specific threshold temperature. In Canada, common threshold values are around 17°C or 18°C. Higher HDD values indicate a greater demand for heating in the space (ClimateData, n.d.).

To determine the daily Cooling Degree Days (CDD) and Heating Degree Days (HDD), our initial step involves gathering daily average temperature data from the Climate dataset provided by Environment and Climate Change Canada. Specifically, we utilize the daily data obtained from Woodstock station located in New Brunswick. Subsequently, we employ the following formulas to compute monthly CDD and HDD values.

$$CDD_{month} = \sum_{i} (T_i - 18) \tag{4.1}$$

$$HDD_{month} = \sum_{i} (18 - T_i) \tag{4.2}$$

Where T_i represents the daily average temperature, the calculation in this report was performed using monthly data. CDD_{month} and HDD_{month} measure the overall variations between the average daily temperature and the desired comfort level throughout a month. To illustrate, let's consider a scenario where the daily average temperatures in February consistently remain at -10°C; in such a case, HDD_{month} would be computed as follows.

$$HDD_{February} = \sum_{1}^{31}(18 - (-10)) = 31 * 28 = 868 \tag{4.3}$$

If the average daily temperatures in June consistently remain at 20.5°C, the resulting CDD_{June} value would be:

$$CDD_{June} = \sum_{1}^{31}(20.5 - 18) = 2.5 * 31 = 77.5 \tag{4.4}$$

When the HDD value is positive, energy is needed for heating, while a positive CDD value indicates the need for cooling. The HDD value can also be used to establish a correlation between heating costs and temperature: The colder the temperature, indicated by a higher HDD value, the greater the need for space heating (Hor et al., 2005). Take note that in this context, HDD is specifically determined for days when the average daily temperature falls below 18°C. Similarly, CDD is calculated for days where the temperature exceeds 18°C. This intentional approach ensures that both variables exclusively represent positive values, enabling them to effectively measure the additional heating and cooling needs of households, thereby impacting their consumption patterns positively.

Table 4.1 summarizes descriptive statistics of the data used in this report.

Table 4.1. Descriptive statistics of variables

Variable	**Definition**	**Unit**	**Mean**	**Standard deviation**	**Min value**	**Max value**	**Source**
IED	Industrial Electricity Demand	Petajoules	22.57	4.75	13.28	30.33	Canada Energy Regulator (www.cer-rec.gc.ca)
IEP	Industrial Electricity Price	2021 C$ per GJ	18.39	4.72	10.46	28.07	Statistic Canada (www150.statcan.gc.ca)
LI	Labour Income	Current dollars	282.72	29.50	233.60	336.50	Statistic Canada (www150.statcan.gc.ca)
VCAsset	Value of Capital Asset	Dollars	3441	905.29	1822	5642	Statistic Canada (www150.statcan.gc.ca)

VAdded	Value Added Industry	Dollars	24289.91	4675.49	16440.84	32126.6	Statistic Canada (www150.statcan.gc.ca)
T	Monthly Temperature	°C	5.08	10.55	-17.60	21.80	Government of Canada (climate.weather.gc.ca)
CDD	Cooling Degree Days	-		17.62	0	117.80	Part 4.1: Calculation of CDD
HDD	Heating Degree Days	-		319.56	0	1103.6	Part 4.1: Calculation of HDD

4.2. Estimation and Results

In this section, the results of econometric estimations are presented, and discussion of these results is provided.

4.2.1. Model Specification

Since we are using time series data, we have to check for non-stationarity. In this regard, we used the augmented Dickey–Fuller test. Dickey (1979) developed a procedure for testing whether a variable has a unit root or, equivalently, that the variable follows a random walk. There are four different cases to which the augmented Dickey–Fuller test can be applied. The null hypothesis is always that a time series has a unit root or it is non-stationary. Stationary time series is defined as integrated of order zero or I(0). Alternatively, if a time series is non-stationary and exhibits a unit root, it would require differencing to achieve stationarity. In this case, the time series is defined as integrated of order d or I(d), where d represents the number of times the time series needs to be differenced to attain stationarity (Amarawickramaa and Hunt, 2008).

According to the test result, one of the following four approaches can be used: (1) If all variables as time series are stationary, we can run simple OLS regression (2) If all variables are non- stationary but their differences are stationary, we can test for the presence of cointegration; if confirmed, then we can cointegrate them. (3) Third approach is based on the autoregressive process of the following type: we can combine all non-stationary variables under one vector and cointegrate this vector, and use the Error Correction Model (ECM) with the stationary time series; (4) State Space Model (SSM) is a powerful method to capture dynamic behaviour and time-varying characteristics of the consumers. SSM is a mathematical framework that can be used to model and estimate a dynamic system over time. SSM use a two-equation approach where the underlying system is represented by two equations, namely the state equation and the observation equation. The state equation describes how the time-varying parameter change over time (the evolution of unobservable states over time), while the dependent variable is described as a time-varying linear function of independent variables in the observation equation (Arisoy and Ozturk 2014; Guangrong and Yanjun 2011). One important feature of SSMs is the use of the time-varying parameter (TVP) approach with the Kalman filter. This approach allows for more accurate estimations of electricity demand by considering factors like economic activity, price regulation, and structural changes. It also reveals how price and income elasticity change over time. In contrast, traditional time series analysis focuses solely on modeling observed data, while SSM provides a more flexible and comprehensive framework that can handle complex time series patterns, dynamic relationships, and unobserved variables (Aryanpur et al, 2022).

4.2.2. Unit Root Test

In order to assess the potential non-stationary behavior of each individual time series, we employ unit root tests as an initial step. Non-stationarity within the time series can lead to misleading regression outcomes, underscoring the importance of confirming the stationarity of variables. To accomplish this, we utilize the ADF (Augmented Dickey-Fuller) unit root test, which enables us to ascertain whether the variables exhibit stationarity.

The null hypothesis in the ADF test is that the variable possesses a unit root, implying non-stationarity. A p-value greater than 0.05 leads to a failure to reject the null hypothesis, indicating that the variable is non-stationary. In our case, according to the findings presented in Table 4.2, we observe that our variables IED, LI, VAdded and VCAsset possess a unit root, or they are non-stationary.

Table 4.2. Investigation the stationary of variables based on Dicky Fuller unit root test

Variables	**Test Statistic**	**p-value**	**Stationary Status**
IED	-3.14	0.09	Non-Stationary
IEP	-3.46	0.04	Stationary
LI	-3.19	0.08	Non-Stationary
VAdded	-3.04	0.12	Non-Stationary
VCAsset	-2.67	0.24	Non-Stationary
T	-5.20	0.0001	Stationary
CDD	-5.88	0.00	Stationary
HDD	-5.33	0.00	Stationary
Critical values	α=0.01, -3.97 α=0.05, -3.41 α=0.1, -3.13		

To ensure the reliability of our findings, we conducted an additional unit root test to verify the accuracy and consistency of the ADF test. The results of the Philips-Perron test, presented in Table 4.3, align with the outcomes obtained from the ADF test.

Table 4.3. Investigation the stationary of variables based on Philips-Perron unit root test

Variables	**Test Statistic**	**p-value**	**Stationary Status**
IED	-3.21	0.08	Non-Stationary
IEP	-3.47	0.04	Stationary
LI	-3.20	0.08	Non-Stationary
VAdded	-2.98	0.13	Non-Stationary
VCAsset	-2.72	0.22	Non-Stationary
T	-4.72	0.0007	Stationary
CDD	-21.37	0.00	Stationary
HDD	-4.40	0.002	Stationary
Critical values	α=0.01, -3.97 α=0.05, -3.41 α=0.1, -3.13		

After carefully analyzing the time series data and conducting tests to identify the presence of a unit root process (as shown in Table 4.2 - 4.3), we discovered that the majority of time series, with the exception of IEP, T, CDD, and HDD, exhibit a unit root process. This finding implies that our variables are integrated of order one, denoted as I(1). It is crucial to note that incorporating I(1) series in a regression analysis may lead to spurious outcomes, as the regression results might primarily reflect the unit root process among variables instead of explaining authentic relationships among them. In certain scenarios, it is necessary to apply the first difference in order to transform a non-stationary process into a stationary one, commonly referred to as an integrated of order zero, denoted as I(0). However, according to Wooldridge (2015), it is important to note that an integrated of order one process can exhibit either trend-stationarity or difference-stationarity.

Wooldridge (2012) states that a trend-stationary process (TSP) is characterized by being stationary with respect to its time trend and having weak dependence. In contrast, a difference-stationary process (DSP) refers to a sequence of time series that exhibit no trend when considering their first differences, denoted as I(0). Hence, it is necessary to employ various approaches to achieve stationary series. In the case of DSP, the initial difference should be taken into account, whereas for TSP, it is important to consider the incorporation of a time trend (Wooldridge, 2015).

In our analysis, it is evident that the time series variables exhibit a clear pattern of change over time. The ADF test reveals that some variables show first-order integration. When non-stationary variables are included in a regression analysis, it can lead to a potentially misleading relationship between the variables being studied. To address this issue, we followed Woodbridge's (2012) recommendation and applied first difference (diff) to make the non-stationary variables stationary before conducting the regression analysis.

4.2.3. Correlation Matrix Test

A correlation matrix serves as a tabular representation of the outcomes obtained from correlation tests conducted among multiple variables simultaneously. We tackled the issue of multi- and perfect collinearity by employing a correlation matrix and identified a particular set of independent variables. Using the correlation matrix can also help in decreasing the quantity of independent variables as a result of a limited time period.

When collinearity is perfect, it breaks one of the assumptions necessary for unbiased OLS estimators. Although multicollinearity does not introduce bias in the results, it can cause incorrect signs and magnitudes in the estimated coefficients.

In order to tackle the issue of having multi- and perfect collinearity and to restrict the number of explanatory variables, our next step was to construct a correlation matrix (Table 4.4)

Table 4.4. Correlation matrix for independent variables

	IEP	**LI-diff**	**VAdded-diff**	**VCAsset-diff**	**T**	**CDD**	**HDD**	**Summer**
IEP	1							
LI- diff	0.0217	1						
VAdded-diff	0.0071	0.8515	1					
VCAsset-diff	-0.0021	0.3324	0.3535	1				

T	0.020	-0.1601	-0.2104	-0.0333	1			
CDD	0.0020	-0.0350	-0.0469	-0.0097	0.4566	1		
HDD	-0.0197	0.1622	0.2131	0.0336	-0.9987	-0.4124	1	
Summer	-0.0012	-0.0914	-0.1223	-0.0253	0.8553	0.3837	-0.8546	1

When working with time series data, it is essential to ensure that the variables are stationary before computing the correlation matrix test. As previously mentioned, to address this concern, we applied first differencing to remove the unit root and achieve stationarity in the variables. This step helps us obtain more reliable and meaningful insights into the relationships between the variables.

Based on Table 4.4, it is evident that our estimated regression exhibits both multi-collinearity and perfect collinearity issues, as expected. Consequently, we cannot rely on the obtained results. To overcome these problems and enhance the degrees of freedom, one possible approach is to exclude certain independent variables and retain only the most significant ones.

LI-Diff as microeconomic variable is highly correlated with VAdded-Diff, especially in the industrial group. In this regard, we excluded LI-Diff from the microeconomic group during regression. Moreover, to be consistent with the existing literature, our model should definitely include at least one climatic variable and industrial determinants of the electricity market. Thus, we keep microeconomic, industrial and climatic variables in the regression.

From an empirical standpoint, average temperature is one of the strongest determinants of electricity consumption as well as month and the summer dummy.

4.2.4. Industrial Electricity Demand Regression Models

Given that the primary objective of this research was to estimate the relationship between extreme temperatures and the electricity consumption in industrial areas. The regression can be defined by the following expression, where

$$IED_t = (CDD, HDD, X_t) \tag{4-5}$$

X represents a vector comprising price of electricity consumed in the industry, value added, value of capital asset, and labor income. Specifically, the monthly industrial demand was analyzed in relation to these factors through six different specifications. The specifications can be further refined by organizing them into groups based on seasonality, which can be captured using different dummy variables. For example, specifications 2, 4, and 6 incorporate dummy variables to account for the seasonal patterns in industrial electricity demand during summer months.

Specification 1:

$$IED_t\_DIFF = \alpha_1 + \alpha_2 T_t + \alpha_3 IEP_t + \alpha_4 VAdded\_DIFF + \alpha_5 VCAsset\_DIFF + \alpha_6 Month + \varepsilon t \tag{4-6}$$

Specification 2:

$$IED_t\_DIFF = \alpha_1 + \alpha_2 T_t + \alpha_3 IEP_t + \alpha_4 VAdded\_DIFF + \alpha_5 VCAsset\_DIFF + \alpha_6\, Summer + \varepsilon t \tag{4-7}$$

Specification 3:

$$IED_t\_DIFF = \alpha_1 + \alpha_2 CDD_t + \alpha_3 HDD_t + \alpha_4 IEP_t + \alpha_5 VAdded\_DIFF + \alpha_6 VCAsset\_DIFF + \alpha_7 Month + \varepsilon t \quad (4\text{-}8)$$

Specification 4: *(4-9)*

$$IED_t\_DIFF = \alpha_1 + \alpha_2 CDD_t + \alpha_3 HDD_t + \alpha_4 IEP_t + \alpha_5 VAdded\_DIFF + \alpha_6 VCAsset\_DIFF + \alpha_7 Summer + \varepsilon t$$

Specification 5:

$$IED_t\_DIFF = \alpha_1 + \alpha_2 CDD_t + \alpha_3 HDD_t + \alpha_4 CDD_t^2 + \alpha_5 HDD_t^2 + \alpha_6 IEP_t + \alpha_7 VAdded\_DIFF + \alpha_8 VCAsset\_DIFF + \alpha_9 Month + \varepsilon t \quad (4\text{-}10)$$

Specification 6: *(4-11)*

$$IED_t\_DIFF = \alpha_1 + + \alpha_2 CDD_t + \alpha_3 HDD_t + \alpha_4 CDD_t^2 + \alpha_5 HDD_t^2 + \alpha_6 IEP_t + \alpha_7 VAdded\_DIFF + \alpha_8 VCAsset\_DIFF + \alpha_9 summer + \varepsilon t$$

Where:

IED_t = Industrial electricity demand in period t

VAdded = Value added industry

T = Temperature

VCAsset = Value of capital asset

CDD_t = Total cooling degree days for period t

HDD_t = Total heating degree days for period t

Summer = Dummy variable (1: May-September, 0: otherwise

IEP_t : Industrial electricity price

Due to the interdependent nature of the relationship between climate changes, microeconomic factors, and energy demand, it is highly probable that OLS estimations using specifications (4-6)- (4-11) will encounter an issue known as endogeneity. To address the issue of endogeneity, one possible approach is to utilize either the instrumental variable (IV) or two-stage least squares (2SLS) method instead of ordinary least squares (OLS). Both techniques rely on a variable that meets two specific conditions: it must be a strong predictor of the endogenous variable and should have no correlation with the dependent variable. Another method for dealing with the bidirectional relationship between electricity demand and climate changes is to utilize a time series framework (Emodi et al., 2017).

Considering the characteristics of our dataset, we made the decision to employ the OLS (Ordinary Least Squares) technique for estimating our models.

4.2.5. Model Results

We included all independent variables listed in Table 4.5 in the regression using industrial electricity as a dependent variable. We employed the Ordinary Least Squares (OLS) method to estimate our models. Our analysis involved running six different models, which can be categorized into three groups based on our literature review and previous empirical research.

In the first group, the most crucial variable was the monthly temperature. We examined two versions within this group. The first version utilized month along with temperature, while the second variation incorporated summer along with temperature. The second group introduced CDD and HDD as replacements for temperature. Lastly, the third group included squared CDD and HDD terms in addition to the original CDD and HDD variables.

Table 4.5. OLS Model Results

	Group 1		**Group 2**		**Group 3**	
	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**
IEP	-0.0008 (0.0027)	-0.001 (0.0027)	-0.0008 (0.0027)	-0.001021 (0.002794)	-0.00095 (0.0027)	-0.00105 (0.0027)
VAdded_DIFF	0.0001 (8.70E-05)	8.17E-05 (8.64E-05)	9.81E-05 (8.67E-05)	7.76E-05 (8.61E-05)	0.00011 (8.75E-05)	9.42E-05 (8.69E-05)
VCAsset_DIFF	2.67E-05 (0.0001)	2.71E-05 (0.0001)	3.32E-05 (0.000107)	3.54E-05 (0.000108)	2.39E-05 (0.000108)	2.69E-05 (0.000108)
T	0.0025* (0.0013)	0.0063* (0.0024)				
CDD			-0.0003 (0.0008)	-0.000398 (0.000823)	0.000309 (0.002467)	0.000503 (0.002548)
HDD			-9.32E-05* (4.82E-05)	-0.00021* (8.24E-05)	0.000153 (0.000178)	0.000174 (0.000298)
CDD^2					-1.99E-06 (2.88E-05)	-3.89E-06 (2.92E-05)
HDD^2					-2.73E-07 (1.87E-07)	-3.35E-07 (2.43E-07)
Month	0.0091* (0.0040)		0.009139* (0.004083)		0.007628 (0.004210)	

Summer		-0.075 (0.0519)		-0.0721 (0.0515)		-0.008845 (0.068801)
Constant	-0.0826 (0.0591)	- 0.007 (0.0548)	-0.0299 (0.0661)	0.1148 (0.07651)	-0.048 (0.06811)	0.015045 (0.106351)
Durbin-Watson stat	2.01	2.04	2.01	2.04	2.02	2.04
R-squared	0.0192	0.0146	0.0199	0.0152	0.024	0.0183
Adjusted R-squared	0.0114	0.0006	0.0106	0.0058	0.0109	0.0057

***, **, and * represent significance at the 1%, 10%, and 5% levels, respectively. Values in parentheses show Std. Error.

Among the six models considered, group 1 demonstrated highly promising results and the influence of temperature on industrial electricity demand in the province of New Brunswick is both economically and statistically significant.

By incorporating the variable of month, we observed significant coefficients that were consistent with the findings in existing literature. These discoveries hold substantial implications for both the economy and climate change, confirming the existence of a relationship between temperature fluctuations and electricity consumption. To begin our analysis, we initially estimated a linear model within group 1. Also, the temperature in this group has the strongest impact on electricity demand as expected: positive and significant coefficient on T implies that a 1°C increase in the temperature in model A leads to almost

0.002524 Petajoule increase in IED. Then, when we replaced the variable month with summer a 1°C increase in the temperature in model B leads to almost 0.0063 Petajoule increase in IED.

Our next group aimed to enhance the analysis by utilizing the same set of independent variables as Group 2. However, instead of focusing solely on the monthly temperature, we incorporated two additional factors known as CDD and HDD. In model C, after controlling for month, the coefficients on CDD and HDD are both negative and found to be statistically insignificant and significant respectively. In model D, as previous one, only the coefficient on HDD is statistically significant. This suggests that a 1 unit decrease in HDD is associated with a modest increase in IED, estimated to be around 0.00021 Petajoule.

In the earlier sections of this report, we discussed that industrial electricity demand accounts for nonlinearity in the relationship between temperature and quantity of electricity demanded. However, in the case of New Brunswick, it is important to note that Environment Canada utilizes the same base threshold of 18°C for both cooling and heating degree days. Consequently, there is a possibility of nonlinearity in the connections between industrial electricity demand and derived variables.

To illustrate this further, let's consider the scenario where demand for heating decreases as temperatures begin to rise, resulting in a decline in demand at lower levels of CDD. This is due to the reduced requirement for heating during this initial phase. However, once the temperature surpasses a certain threshold, typically at higher CDD levels, there will be an increase in demand to reflect the rising need for cooling. To better capture this relationship, we incorporated a squared term of CDD and HDD in model E and F within group 3.

However, despite our efforts, we found that all the coefficients associated with these squared terms were determined to be statistically insignificant.

As illustrated in Figure 2, our findings reveal a clear linear relationship between temperature and electricity demand. This outcome contrasts with the observed patterns reported in previous studies (Franco and Sanstad (2008); Fonseca et al. (2019); Moral-Carcedo and Vic´ens-Otero (2005)), which suggested a U-shaped pattern in the relationship between CDD, HDD, and industrial electricity demand.

Therefore, our results provide new insights that challenge the existing literature by demonstrating that the relationship between temperature and electricity demand does not follow a U-shaped trend. However, Li et. all (2018), which looked at the relations of total electricity consumption to climate change in Nanjing, observed a similar relationship between HDD and energy consumption similar to ours. One important reason for the differences in our findings is that we looked at different things compared to previous research. For instance, we considered various factors that others might not have taken into account. While most studies focused on residential electricity use, we also looked at industrial electricity consumption. This difference in what we examined and the extra factors we considered plays a big role in why our results are not the same as what others have found.

In our analysis, we enhanced the model by incorporating two important dummy variables: month, and summer. Additionally, we analyze the Durbin-Watson statistic for all the models, and the values obtained are approximately 2. The Durban-Watson statistic quantifies the level of autocorrelation within the error terms of a model, using a scale ranging from 0 to 4 (Brown and Hambley, 2002). A value of 2 indicates the absence of autocorrelation, whereas values below 2 indicate the presence of positive autocorrelation, and values above 2 indicate the presence of negative autocorrelation (Hewings et al, 2002).

We generate month as dummy for each year and to account for seasonal variations in industrial electricity demand, we incorporated a dummy variable specifically for the summer months (May to September) in certain model specifications. The average temperature in New Brunswick seldom exceeds 18°C except during the summer months. As a result, occurrences of CDD above zero are primarily observed in the summer season. This statistical relationship indicates a strong correlation between CDD and the dummy variable. Consequently, the introduction of CDD in specifications might have led to the insignificance of the coefficients associated with the dummy variable. So, it is important to acknowledge the presence of seasonality. Instead of using the variable month, it would be more appropriate to incorporate the term summer in models B, D, and F.

Price and value added of industry effect:

Based on the law of demand, the relationship between the price of a commodity and its quantity demanded is inverse. When the actual price declines, consumers become less responsive to price fluctuations. We discovered an inverse relationship between electricity price and demand across all specifications.

Additionally, electricity is considered a normal commodity, so as people's income increases, their electricity consumption also tends to rise. When we consider the effects of substitution and income, which align in the case of a normal commodity, a lower the actual price of electricity leads to a higher in consumption due to both the income and substitution effects working in the same direction (Aryanpur et al., 2022). When we consider the effects of both income and substitution, a decrease in the price of a normal commodity like electricity can lead to an increase in consumption. This is due to the alignment of the income and substitution effects, both working in the same direction.

The substitution effect focuses on how changes in relative prices impact consumer choices. When the price of electricity decreases, it becomes relatively cheaper compared to other goods. This prompts consumers to substitute some of their previous consumption of more expensive goods for electricity, leading to an increase in electricity consumption. In other words, consumers switch to the cheaper option to maximize their utility.

The income effect takes into account the change in purchasing power due to price changes. When the price of electricity decreases, consumers effectively have more purchasing power because they can buy the same amount of electricity for less money. This increase in purchasing power allows consumers to afford more goods, including electricity. Therefore, they increase their consumption of electricity due to the increase in real income.

In the case of a normal commodity, both the income and substitution effects work together to amplify the increase in consumption resulting from a decrease in the price of electricity. The decrease in price makes electricity relatively cheaper (substitution effect), and the increased purchasing power makes it more affordable (income effect). Since both effects reinforce each other in encouraging higher consumption, it's likely that the overall response to a price decrease will be an increase in electricity consumption.

The findings indicate that a rise of CAD$1 in VAdded would lead to a surge in the electricity consumption of the industrial sector, specifically by 0.0001 Petajoules. Therefore, these basic observations lead us to highlight VAdded variable in influencing industrial demand. Therefore, our findings demonstrated that the coefficients exhibit the expected signs in line with the law of demand, and they are accompanied by corresponding p-values.

Chapter 5: Conclusions

New Brunswick is currently witnessing the consequences of a changing climate, and these impacts are expected to increase in the future. The existing greenhouse gas levels in the atmosphere are projected to persist for many years, further influencing weather patterns that result in higher temperatures, increased rainfall, rising sea levels, and more severe weather occurrences. Moreover, the debate surrounding the Trans Mountain pipeline expansion in Canada illustrates the complexities of climate change mitigation. Supporters argue for economic benefits through job creation and cost reduction, while opponents' express concerns about meeting emission targets. However, the discourse often overlooks the bidirectional relationship between energy consumption and climate change. While energy production contributes to global warming, weather pattern changes impact energy supply and demand. For instance, higher temperatures can lower heating demands, affecting electricity consumption. Neglecting climate-induced shifts in electricity demand could lead to ineffective mitigation strategies.

So, it is imperative for New Brunswick to prepare and adapt to forthcoming climate conditions in order to minimize the impact on communities, natural resources, and infrastructure, while safeguarding public health and safety. In this report, we have analyzed the climate change impacts on industrial electricity demand in New Brunswick.

To identify the economic consequences of climate change outcomes on industrial electricity, we have used the time series data analysis framework and collected microeconomic, industrial and climate data for the period of fifty-two years from 1970 to 2022. We also included New Brunswick's real price of electricity, value of capital assets, labour income, and industrial value added in our regressions to control for standard demand factors such as income and price. The effect of climate change on electricity demand has been studied in numerous regions worldwide (refer to Emodi et al. 2019; Pantely and Mancarella 2015; Mideksa and Kallbekken 2010; Schaeffer et al. 2012 for detailed regional analyses). While our study does not encompass a complete comparison with all prior research, it is valuable to situate our findings within a global framework.

The production function is used to derive a standard industrial electricity demand equation as factor demand, in which the energy price and income are the explanatory variables. Although the proposed method is used for the case of New Brunswick, it can be used to support climate change impacts in other cities and countries. To estimate our models, we utilized the Ordinary Least Squares (OLS) method. Our analysis comprised six distinct models, which can be classified into three groups.

Following ADF and correlation matrix tests, we've taken steps to address issues in our regression analysis. The ADF test identified first-order integration in certain variables, raising concerns about misleading relationships when including non-stationary variables. To mitigate this, we employ first differencing to convert a non-stationary variable into a stationary.

Subsequently, we regressed the set of independent variables against industrial electricity demand. Group 1 exhibited promising outcomes, emphasizing the significant impact of temperature on New Brunswick's industrial electricity demand. By introducing month variable, we observed consistent and noteworthy coefficients. Noteworthy in model A, the positive and significant coefficient of T verifies that a 1°C temperature increase corresponds to an approximate 0.002722 Petajoule surge in industrial electricity demand.

In addition to the above results, the findings show that an inverse relationship was found between electricity price and demand in all specifications. Moreover, as people's income increases, their electricity consumption tends to rise, indicating that electricity is considered a normal commodity. These observations emphasize the importance of the VAdded variable in influencing industrial demand.

Further research on the effects of climate change on industrial electricity demand in New Brunswick can focus on examining both the supply and demand aspects. On the supply side, investigating the potential impacts of renewable energy integration and energy storage technologies on the reliability and availability of electricity supply in the face of changing climate conditions would be valuable. Future investigations might explore how the cost savings achieved by mitigating the impact of climate change on industrial electricity demand can be strategically utilized for public investments, potentially leading to enhanced economic growth.

Chapter 6: Lessons and future work with the existing content

This section discusses lessons learned from the approach used in this study. First, there are four primary theoretical approaches commonly used to derive industrial energy demand. These approaches include the Aggregate Production Function method, General Equilibrium analysis, Partial Equilibrium analysis, and Ad hoc or Econometric Methods. However, in the present analysis, we focus on the Production Function method as it offers a comprehensive framework to explain economic output based on input factors of production. By employing this method, we can derive the factor demand for industrial electricity directly from the production function.

It is important to note that the utilization of alternative approaches can be quite challenging in this context. Nevertheless, the Production Function method stands out by explicitly capturing the relationship between energy demand and economic output. This method provides valuable insights that significantly contribute to the decision-making process with confidence.

Second, it is worth discussing that this report serves as a valuable resource for decision-makers seeking to gain a comprehensive understanding of the extent to which a policy intervention has achieved its original goals. In New Brunswick, the effects of climate change have become increasingly evident in recent years, as highlighted by the compelling evidence provided by Specifications 1 and 2. Therefore, it is crucial for decision-makers to prioritize sustainable energy initiatives to safeguard the well-being of future generations.

Furthermore, decision-makers should consider investing in innovative technologies and exploring avenues that enable us to mitigate and minimize the impact of climate change on electricity demand. Merely waiting for solutions to materialize is insufficient they must proactively and responsibly seek out new non-emitting technologies capable of alleviating the burdensome penalties associated with carbon emissions. Consequently, we are actively directing our investments towards research and development opportunities that hold the potential to address this pressing issue effectively.

The current study has several limitations that should be considered in future research. One important limitation is the lack of accounting for regime change, specifically the omission of the 2007-2008 economic crisis. Economic crises can have a significant impact on the variables under investigation and can introduce changes in the relationships between them. To overcome this limitation, future studies should include a dummy variable that reflects the occurrence of the economic crisis, allowing researchers to assess its effects on the variables of interest and adjust for any potential changes in coefficients during that time period.

Moreover, it is important to highlight the presence of both I(0) and I(1) variables in our study. Although the preferred choice might have been the ARDL model, we opted for OLS. To address this limitation, it's recommended that future research employs the ARDL approach and compares the results. This comparison could provide a more comprehensive understanding of the relationships and strengthen the overall robustness of the findings.

Another limitation is the break in the data that occurred in 2020, which has the potential to alter coefficients. The specific details surrounding this break are not provided, but it is important to acknowledge that breaks in the data can signify shifts in the underlying relationships between variables. Future studies should carefully examine the circumstances surrounding the break in 2020 and consider incorporating appropriate adjustments or control variables to capture its effects. Additionally, it is crucial to assess whether the coefficients differ significantly before and after the break, providing insights into potential changes in the relationship between the variables.

These limitations highlight the need for further investigation in future studies to address regime changes, economic crises, and breaks in the data. By addressing these limitations, researchers can enhance the validity and robustness of their findings, leading to a more comprehensive understanding of the variables being studied.

Another area of future research would be to investigate that solely data in public access is used in this report. would be advisable to examine additional data sources that are not publicly available but could potentially influence electricity demand. Further efforts should be dedicated to expanding the regional dataset and refining the econometric model in order to enhance its accuracy. Although the methodology and projections are not completely invalidated by these limitations, they do highlight deficiencies that should be considered.

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Appendix

The Lagrange multipliers method is used for constrained optimization we can modify our optimization set up as follow (let's call it G):

$$\text{Min } G = C + \lambda\,(Q - f\,(K, L, E, \text{A})) \tag{A.1}$$

Which becomes:

$$G = P_k K + P_l L + P_e E + P_a A + \lambda\,(Q - AK^{\alpha} L^{\beta} E^{\gamma} A^{\eta}) \tag{A.2}$$

Based on Lagrange multipliers method next we should calculate the partial derivatives of the function *G* with respect *L, K, E, A,* and λ. The partial derivatives are given below:

$$G'_{\lambda} = Q - AK^{\alpha} L^{\beta} E^{\gamma} A^{\eta}$$

$$G'_{L} = P_l - \lambda A \beta K^{\alpha} L^{\beta-1} E^{\gamma} A^{\eta}$$

$$G'_{K} = P_k - \lambda A \alpha K^{\alpha-1} L^{\beta} E^{\gamma} A^{\eta}$$

$$G'_{E} = P_e - \lambda A \gamma K^{\alpha} L^{\beta} E^{\gamma-1} A^{\eta}$$

$$G'_{A} = P_a - \lambda A \eta K^{\alpha} L^{\beta} E^{\gamma} A^{\eta-1} \tag{A.3}$$

To find the extremum point, we must first equate all of the above derivatives to zero:

$$Q - AK^{\alpha}L^{\beta}E^{\gamma}A^{\eta} = 0$$

$$P_l - \lambda A\beta K^{\alpha}L^{\beta-1}E^{\gamma}A^{\eta} = 0$$

$$P_k - \lambda A\alpha K^{\alpha-1}L^{\beta}E^{\gamma}A^{\eta} = 0$$

$$P_e - \lambda A\gamma K^{\alpha}L^{\beta}E^{\gamma-1}A^{\eta} = 0$$

$$P_a - \lambda A\eta K^{\alpha}L^{\beta}E^{\gamma}A^{\eta-1} = 0 \qquad \text{(A.4)}$$

Then, taking logs of both sides, and we can get following system of equations:

$$\ln Q = \ln A + \alpha lnK + \beta lnL + \gamma lnE + \eta lnA$$

$$lnP_l = \ln\lambda\beta A + \alpha lnK + (\beta - 1)lnL + \gamma lnE + \eta lnA$$

$$lnP_k = \ln\lambda\alpha A + (\alpha - 1)lnK + \beta lnL + \gamma lnE + \eta lnA \qquad \text{(A.5)}$$

$$lnP_e = \ln\lambda\gamma A + \alpha lnK + \beta lnL + (\gamma - 1)lnE + \eta lnA$$

$$lnP_a = \ln\lambda\eta A + \alpha lnK + \beta lnL + \gamma lnE + (\eta - 1)lnA$$

Since, our goal is to derive a formula for the Energy Demand Function, we must express all other variables in terms of energy demand, namely E. For this, first, we express L in terms of E by subtracting the fourth equation of the system (A.5) from the second one and using the properties of logarithmic function. This yield:

$$ln\frac{P_l}{P_e} = ln\frac{\beta}{\gamma} - lnL + lnE \qquad \text{(A.6)}$$

Modifying this equation, a little we can derive a formula relating L to E:

$$lnL = -ln\frac{P_l}{P_e} + ln\frac{\beta}{\gamma} + lnE \quad Or \quad lnL = ln\frac{P_e}{P_l}\frac{\beta}{\gamma}E \tag{A.7}$$

Therefore:

$$L = \frac{P_e}{P_l}\frac{\beta}{\gamma}E$$

Similarly, by subtracting the fourth equation from the third and fifth equations, we obtain the formulas relating K and A to E:

$$K = \frac{P_e}{P_k}\frac{\alpha}{\gamma}E \tag{A.8}$$

And

$$A = \frac{P_e}{P_a}\frac{\eta}{\gamma}E \tag{A.9}$$

Considering (A.7), (A.8) and (A.9) in the first equation of the system (A.5) we end up with:

$$\ln Q = \ln A + \alpha ln\frac{P_e}{P_k}\frac{\alpha}{\gamma}\ E\ + \beta\ ln\ \frac{P_e}{P_l}\frac{\beta}{\gamma}\ E + \gamma\ lnE\ + \eta\ ln\frac{P_e}{P_a}\frac{\eta}{\gamma}E \tag{A.10}$$

We can re-express (A.10) using the logarithmic function's properties:

$$\ln Q = \ln A + \alpha \ln\left(\frac{P_e}{P_k}\right) + \alpha \ln\left(\frac{\alpha}{\gamma}\right) + \alpha\ lnE\ + \beta\ ln\ \left(\frac{P_e}{P_l}\right) + \beta \ln\left(\frac{\beta}{\gamma}\right) + \beta\ lnE + \gamma lnE\ + \eta \ln\left(\frac{P_e}{P_a}\right) + \eta \ln\left(\frac{\eta}{\gamma}\right) + \eta \ln E \tag{A.11}$$

By combining the constant terms and *lnE* coefficient in equation (A.6), we can obtain:

$$\ln Q = \ln A + [\alpha \ln\left(\frac{\alpha}{\gamma}\right) + \beta\, ln\left(\frac{\beta}{\gamma}\right) + \eta\, ln\left(\frac{\eta}{\gamma}\right)] + \alpha\, ln\left(\frac{P_e}{P_k}\right) + \beta\, ln\ \left(\frac{P_e}{P_l}\right) + \eta\, ln\left(\frac{P_e}{P_a}\right) + [\alpha + \beta + \gamma + \eta]\, lnE \tag{A.12}$$

Let's find *lnE* from this expression:

$$[\alpha + \beta + \gamma + \eta]\, lnE = \ln Q - \ln A\ \ [\alpha \ln\left(\frac{\alpha}{\gamma}\right) + \beta\, ln\left(\frac{\beta}{\gamma}\right) + \eta\, ln\left(\frac{\eta}{\gamma}\right)] - \alpha\, ln\left(\frac{P_e}{P_k}\right) - \beta\, ln\ \left(\frac{P_e}{P_l}\right) - \eta\, ln\left(\frac{P_e}{P_a}\right) \tag{A.13}$$

We can modify (A.13) as follow:

$$[\alpha + \beta + \gamma + \eta]\, lnE = \ln Q - \ln A + \ [\alpha \ln\left(\frac{\gamma}{\alpha}\right) + \beta\, ln\left(\frac{\gamma}{\beta}\right) + \eta\, ln\left(\frac{\gamma}{\eta}\right)] + \alpha\, ln\left(\frac{P_k}{P_e}\right) - \beta\, ln\ \left(\frac{P_l}{P_e}\right) - \eta\, ln\left(\frac{P_a}{P_e}\right) \tag{A.14}$$

Using some mathematical features of the logarithmic function and dividing both sides by the *lnE* coefficient, we obtain:

$$lnE = \frac{1}{[\alpha+\beta+\gamma+\eta]} \ln Q - \frac{1}{[\alpha+\beta+\gamma+\eta]} \ln A + \frac{[\alpha \ln\left(\frac{\gamma}{\alpha}\right)+\beta\, ln\left(\frac{\gamma}{\beta}\right)+\eta\, ln\left(\frac{\gamma}{\eta}\right)]}{[\alpha+\beta+\gamma+\eta]} + \frac{\alpha}{[\alpha+\beta+\gamma+\eta]}\, ln\, P_k + \frac{\beta}{[\alpha+\beta+\gamma+\eta]}\, ln\, P_l + \frac{\eta}{[\alpha+\beta+\gamma+\eta]}\, ln\, P_a + \frac{[-\alpha-\beta-\eta]}{[\alpha+\beta+\gamma+\eta]}\, P_e \tag{A.15}$$

Equation (A.15) can be represented as follows, with new letters used to indicate coefficients:

$$lnE = \alpha_0' + \alpha'\ ln\, P_k + \beta'\ ln\, P_l + \eta'\ ln\, P_a + \gamma'\ ln\, P_e + \delta' lnQ \tag{A.16}$$

Equation A.16 is a derived formula for industrial energy demand that expresses it as a function of labour, capital, climatic variable, and energy prices, as well as industrial output. According to (Nordhaus, 1975), the economy's demand functions for each good can be expressed as follows:

$$Q_i = f^i (P_1, P_2, P_3, P_4, \ldots P_n, V), i=1, \ldots, n \tag{A.17}$$

P_i represents the price, while V represents value added, respectively. This function (with variables in logs) can be written explicitly as:

$$lnQ_i = \theta_0 + \theta_1 \ln P_k + \theta_2 \ln P_l + \theta_3 \ln P_a + \theta_4 \ln P_e + \theta_5 lnV \tag{A.18}$$

If we substitute lnQ in (A.16) with its expression in (A.17) it yields to:

$$lnE = \alpha_0' + \alpha' \ln P_k + \beta' \ln P_l + \eta' \ln P_a + \gamma' \ln P_e + \delta' (\theta_0 + \theta_1 \ln P_k + \theta_2 \ln P_l + \theta_3 \ln P_a + \theta_4 \ln P_e + \theta_5 lnV) \tag{A.19}$$

Equation (A.19) can be written in the following simplified form:

$$lnE = \alpha_0^{"} + \alpha^{"} lnP_k + \beta^{"} lnP_l + \gamma^{"} lnP_e + \eta^{"} lnP_a + \delta^{"} lnV \tag{A.20}$$

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