Msc Thesis

Tilburg School of Economics and Management

Impact of Temperature Rise On Electricity Consumption of Nordic Countries

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February 2021

Abstract

One of the main aspects of climate change is temperature rise. It has a direct effect on electricity consumption. This study investigates the relationship between electricity demand and temperature in Nordic countries which are Norway, Sweden, Finland and Denmark. I use daily data on electricity consumption from Nord Pool and mean temperature from countrys' methodological institutes. I create 5 temperature intervals to analyze the relationship at each interval. Post Double Selection method is used to analyze the impact. Results suggest that temperature rise has a negative effect below 20°C whereas the effect turns to positive above 20°C. In addition, the strongest negative effect is seen between -10°C and 10°C due to intensity of diminishing heating effect. This study contributes to the literature methodologically.

Acknowledgements

First and Foremost, I would like to express my special thanks of gratitude to Dr. Madina Kurmangaliyeva for her guidance and encouragement during thesis process.

Secondly, I am extremely grateful to my family for their love, caring and sacrifices for educating and preparing me for my future. Also, I express my special thanks to my uncle, Dr. Özhan Öztuğ for being a role model for me in my life.

Last but not least, I would like to thank my close friends who always psychologically support me during hard times.

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1 Introduction

The global temperature is expected to rise by 1.5°C to 2.3°C above 1850−1900 period (IPCC (2014)), which is the precise effect of climate change. Statistics show that the planet's average surface temperature has already risen about 1.14°C since late 19th century(NASA (2020)). Besides, the global temperature rise is also causing changes in hydrological cycles, rise in sea levels, higher occasions of extreme weather events, which are seen as other consequences of climate change.

Rising temperatures are likely to affect both the demand and supply of electricity, especially in Nordic countries whose electricity supply is mostly coming from renewable energy resources. According to the Nordegio (Nordic Research Center)'s statistics, their energy consumption mostly depends on residential and commercial electricity and oscillates around 50 GJ/per capita. In contrast, this number is 20 GJ/per capita for the rest of Europe and 10 GJ/per capita globally. The high consumption is expected to decrease with the increase in temperature. Hence, less consumption leads to a reduction in electricity demand. On the other hand, on the supply side, temperature rise might cause more water to evaporate into the air. Therefore, warmer air holds more water to vapour, leading to heavy rains resulting in extreme water flow, primary resource of hydropower. Since the effect of temperature rise might be the opposite of demand and supply, it is possible to imbalance them. Chattopadhyay, Bazilian, and Chattopadhyay (2019) states; "Together, these risks can lead to power outages, increased electricity prices and increased maintenance, and capital costs - along with damaging economic, environmental, and public health consequences,".

Given those facts, I am investigating the impact of temperature rise on electricity consumption in Nordic Countries in this study and answering the question: Will electricity consumption increase or decrease with temperature increase in Nordic Countries?

Bessec and Fouquau (2008) conduct a study to answer this question by applying panel threshold regression model on three on 15 European countries between 1985-2000. They divide countries into three categories as warm, intermediate and cold countries. Their results suggest that temperature increase decreases the electricity consumption in the cold regime, whereas it increases electricity consumption in the warm regime. However, Bessec and Fouquau (2008) do not take into account regional electricity consumption data. This study's first main difference from Bessec and Fouquau (2008) is the consideration of regional data. The second one is the analyzing the relationship at different temperature intervals instead of looking at only two regimes.

I obtain daily electricity consumption data of different Nordic Countries' regions from Nord Pool between 2013 and 2019. Also, I collect the daily mean temperatures from methodological institutes of Nordic countries regarding the areas in Figure 3. Also, I create dummies of months, days and holidays to remove seasonality, working days and holidays on the relationship between temperature and electricity consumption. I make five temperature intervals to analyze the relationship. I use Post Double Selection method by Belloni, Chernozhukov, and Hansen (2013) to examine the impact of temperature rise on electricity consumption. It is a method that consists of 3 steps. In the first two steps, I use Lasso regression for variable selection. In the final step, I apply OLS regression with selected variables.

Results show that temperature rise leads to a decrease in electricity consumption up to 20°C, whereas it has a positive effect above 20°C. The diminishing heating effect and emergence of cooling effect plays a crucial role in the relationship at different temperatures.

This study contributes to the literature by providing results for the last decade for Nordic countries in this context. There is no such a study in this context that considering regional differences in consumption in Nordic countries. Besides, it uses a new method that combines prediction and inference tasks to give more unbiased results than traditional methods. However, like every study, it has limitations. The limitations are the unavailability of regional data for Finland and not considering the growth in GDP and population.

The outline of the thesis is as follows; I discuss previous studies in the literature review part. Secondly, I present the data and design of the model in the Data and Methodology part. Thirdly, I present the results and interpret them in the Results part. Lastly, I discuss the study and make policy recommendations in the Conclusion part.

2 Literature Review

Research studies on the influence of temperature rise on electricity demand have mainly focused on the change in electricity demand caused by the heating and cooling behaviors in buildings and the residential sector, mainly focusing on developed countries and regions (Fan, Hu, & Zhang, 2019). As a global study,Eni, Mattei, Cian, Lanzi, and Roson (2007) investigate the climate change impacts on energy demand for 31 countries. Their results suggest that 1% increase in the temperature reduces the annual energy demand by 0.508% for cold countries, Canada and Nordic Countries. On the other hand, the demand will increase for the mild and warm countries because of the cooling effect.(the effect of climate discomfort due to higher base temperatures on the need of cooling)

Country wise studies conducted for the European area are mainly based on scenarios and simulations using regression methods.Mideksa (2009), Pilli-sihvola, Aatola, Ollikainen, and Tuomenvirta (2010), Hor, Watson, and Majithia (2005) and Fan et al. (2019) are four studies that use degree days approach in method. Hor et al. (2005) choose multiple regression over ANN and B&J method for forecasting monthly electricity demand and analyzing the relationship between weather change and electricity demand for England and Wales from 1989 to 2003. Using socioeconomic variables provided a better understanding of the relationship. A strong correlation is found between electricity demand growth, GDP growth, and population growth. Differently, Mideksa (2009) conducted the study based on IPCC's A1b (balanced across all resources) scenario. They divided days into two categories; HDD(heating degree days-above baseline temperature) and CDD(cooling degree days-below baseline temperature), and did empirical statistical downscaling (E-SDS) to decrease HDD by 700 and increase CDD by 120 at the city level in the period of 2000 to 2100. Also, Electricity price and income are used as instrumental variables in the model. Result suggests that if there are a unit increase in CDD and HDD, electricity consumption increases by 0.04 % and 0.01 %, respectively. In addition, Pilli-sihvola et al. (2010) account for non-linearities by also using HDD and CDD. Projection from 2071 to 2100 is based on 1 Celsius degree increase in global temperature. According to their results, 1 degree Celcius increase in temperature leads to 1.8 % increase in electricity demand, starting from a temperature above +21°C. On the other hand, a temperature decrease of 1°C causes electricity demand to increase about 1.4 % in places where the temperature is below 12°C. The main reason is diminishing the need for heating, especially in Northern and Central Europe. Similarly, Fan et al. (2019) apply the same method to China by using a panel data consisting of 30 regions from 1995 to 2016. Regression results showed that an increase in the CDD by 1 % increases per capita electricity demand by 0.063% in China whereas the elasticity coefficient is 0.033 % for the HDD. Moreover, the scenario with high emission without intervention results suggest that there might be an increase in the demand about 518.58 billion kWh ,which is 7.5 higher than the other two scenarios by IPCC (2014).

Another study by Damm, Köberl, Prettenthaler, Rogler, and Töglhofer (2017) criticize degree days approach and used Smooth Transition Regression (STR) by using the corrected electricity consumption data and population weighted temperature data for each country from 2006 to 2013. Authors give point to importance of non-climatic factors such as efficiency of electricity use on the impact. Findings suggest that climate change will have a positive effect on electricity demand in the sense of less usage of electricity if there will be no switch to cooling intensive lifestyle or abandon electric heating. The highest decrease is found for Norway with up to 5.2% followed by other Nordic and some other European countries. On the other hand,Doshi, Abdullah, and Studies (2015) use hour-by-hour modeling approach for the estimation of the relationship between electricity demand and climate variables from 2003 to 2012. High number of observations by hourly separate models provide an hourly analysis of the effect. Findings of the model suggest that the effect of future climate change on average electricity demand might be higher than peak demand in Singapore. The main reason is that SR and LR temperature elasticies are larger during the night because of residential overall load.

My approach focuses only on electricity consumption unlike Eni et al. (2007)'s energy demand function consists of multiple energy goods. Besides, there are not any scenarios/simulations as Damm et al. (2017) did. However, it is taking regional differences in temperature and electricity consumption into account.

3 Data and Methodology

This section includes information about data sources structure and methods used in thesis.

3.1 Data

The study uses Nordpool electricity consumption and temperature data from countries' methodological institutes between January 2013 and December 2019. The measurement of the data is daily.

3.1.1 Electricity Consumption Data

Nord Pool is a power market which offers trading, clearing, settlement and associated services in intraday and the day-ahead market for Nordic, Baltic and some European countries. It also provides region-wise markets to Nordic countries, except Finland. (See Figure 3). I obtain daily electricity consumption data measured in MW of Nordic Countries through the link;

`www.nordpoolgroup.com/historical-market-data/`

3.1.2 Temperature Data

I collect daily mean temperature data from the country's methodological institutes. I choose the location of weather stations based on most populated cities in Nord Pool market areas. Table 1 shows the cities I choose based on the population. As there is no available station around populated locations in area 3 of Norway, I exclude it. Also, I obtain Helsinki data for Finland because Nord Pool does not provide region-wise markets in Finland.

The main reason why I choose most populated cities is the major sectors' location. According to statistics of Nordic Energy Research (2012), three main sectors that consume the most of electricity are industrial, transportation, and buildings' heating and cooling systems. (See Figure 4) Since buildings' heating/cooling and transportation sector is in cities, I analyze industrial sectors' location to eliminate the differences between industrial areas and cities. Industrial areas are mainly located around/between cities. Oslofjord area which is just below Oslo is home for Norway's industries.

Fifty per cent of industries are located there. Other industrial areas are located around major cities along the coast as far north as Trondheim. For Sweden, industrial areas are located in the south of the country where most cities are located. On the other hand, Denmark is too small compared to other Nordic countries, so there is no considerable temperature difference between industrial areas and cities. On the other hand, industrial regions in Finland are at the south of the land, mostly between Turku, Tampare and Helsinki. This eliminates the over/under fitting caused by temperature difference even though Finland does not have region-wise data.

Area	Norway	Sweden	Denmark	Finland
1	Oslo	Lulea	Aarhus	Helsinki
2	Stavanger	Stockholm	Kopenhagen	-
3	-	Jonkopings	-	-
4	Tromso	Malmö	-	-
5	Bergen	-	-	-

Table 1: Location of weather stations

Norway Norwegian Meteorological Institute(`www.met.no`) has several weather stations all over the country. Even though some stations stop functioning, the ones inside big cities are active. There are 5 Nord Pool market areas in Norway. However, there is no data between 2019 and 2013 for area 3 where Alesund and Trondheim are located. Besides, for area 2, I use Stavanger as a location because there is no data for Kristiansand. (See Appendix 5 for the exact locations of stations on Google Map)

Sweden There are 4 Nord Pool market areas for Sweden. I obtain daily mean temperature data from he Swedish Meteorological and Hydrological Institute(`www.smhi.se`). Table T1 shows the cities where weather stations are located. Most populated cities are located in the coastline of the country. (See Appendix 5)

Finland Nord Pool data provides countrywide consumption data for Finland. Because of that, I obtain data for the capital city, Helsinki as the central location from `en.ilmatieteenlaitos.fi/`.

There are several reasons. Firstly, according to Statista, Helsinki has 653,835 inhabitants. This number is 2.25 times higher than the number of inhabitants of the second largest city, Espoo. Also, Espoo and Vantaa (fourth-largest city) is very close to Helsinki. This means that most of the population live around Helsinki. Secondly, the distance between Helsinki and second-largest city, Tampere is 180 km which is very low. Hence, it can be said that the temperature difference between most populated cities and the industrial area of Finland is at the minimum level.

Denmark I collect data for Aarhus and Kopenhagen in Denmark from `www.dmi.dk`. Since Denmark is a small country unlike other Nordic countries, the temperature difference between areas are lower compared to other Nordic countries. (See Appendix 5)

3.1.3 Set Of Confounders

I use several dummy variables to remove the effect of non-climatic factors on electricity consumption. Unlike Bessec and Fouquau (2008), I create dummy variables for each month and day. By doing this, I control the seasonality related to the activity more effectively. Also, in the line with Moral-Carcedo and Vicéns-Otero (2005) , using day dummies helps to capture the activity during working days. Since I obtain regional data among countries, I create dummies for each region to capture average response for a large geographical area considering regional differences in temperature. Besides, I create a variable called $Temp_{Range}$ to prevent multicollinearity caused by max and min temperature variables by subtracting maximum temperature from minimum temperature on a specific day. It represents the range length of temperature on a day. It captures the daily fluctuations on electricity consumption. Lastly, I use holiday dummy which represents public holidays in Nordic countries to remove the change in consumption due to decrease in the activity during holidays.

3.1.4 Relationship between Temperature and Electricity Consumption

As Nordic countries are among top cold countries in the world, the relationship between temperature and electricity consumption is negative. Figure 1 displays the scatter plots of electricity consumption against temperature for Nordic cities located in Nord Pool market areas. Although all graphs exhibit same pattern, there are clear differences between them regarding the reaction of households,industry levels and temperature differences.

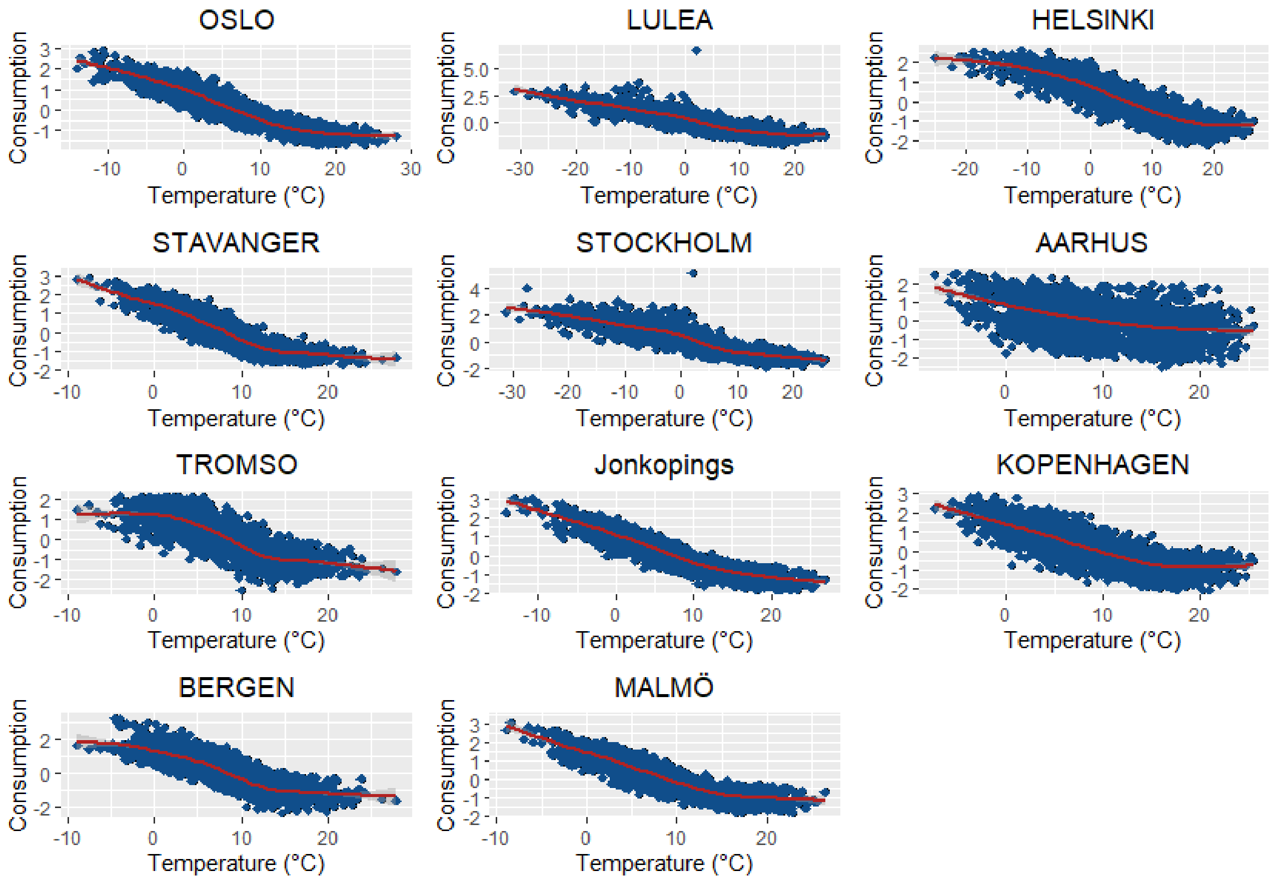

Figure 1: Relationship between Temperature and Electricity Consumption

Level of diminishing heating effect through temperature increase varies between cities. Heating effect is the reduction effect of heating systems in buildings on electricity consumption with rising temperature levels. Colder cities tend to have higher slopes whereas cities located in south of the map tend to have lower slopes at cold regime. For instance, Oslo, Malmö or Kopenhagen has higher slope compared to Tromso or Lulea. (See Table 1 for temperature statistics). This means that the speed of diminishing heating effect is higher in more warmer areas because the regime change happens more faster than others.

According to Figure 1, most of the cities have an inflexion point between 10°C-15°C. This point represents the regime change from cold to warm. However, after this point,the response of electricity consumption to temperature increase decreases. The relationship turns almost to neutral relationship. The reason is the emergence of cooling effect. Although Nordic countries has long winters, district cooling market has grown in the Nordic countries (Patronene Jenni, Kaura, and Torvestad (2017)). On the other hand, industry shutdowns for summer holiday have also an effect on the negative relationship. For instance, industrial production stops for two to three weeks in July in Norway. Even though this strengthens the negative relationship, emergence of cooling effect dominates.

3.1.4.1 Descriptive Statistics

Table 2: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Temperature	27,163	7.311	7.847	−31.100	1.821	13.600	28.000
Consumption	28,116	84,785.670	65,666.610	17,583	41,330.5	102,895.2	379,797
$Temp_{Range}$	28,116	6.889	3.763	0.400	3.900	9.200	22.6
Oslo	28,116	0.091	0.287	0	0	0	1
Stavanger	28,116	0.091	0.287	0	0	0	1
Tromso	28,116	0.091	0.287	0	0	0	1
Bergen	28,116	0.091	0.287	0	0	0	1
Lulea	28,116	0.091	0.287	0	0	0	1
Stockholm	28,116	0.091	0.287	0	0	0	1
Jonkopings	28,116	0.091	0.287	0	0	0	1
Malmö	28,116	0.091	0.287	0	0	0	1
Aarhus	28,116	0.091	0.287	0	0	0	1
Kopenhagen	28,116	0.091	0.287	0	0	0	1
Helsinki	28,116	0.091	0.287	0	0	0	1
January	28,116	0.085	0.279	0	0	0	1
February	28,116	0.077	0.267	0	0	0	1
March	28,116	0.085	0.279	0	0	0	1
April	28,116	0.082	0.275	0	0	0	1
May	28,116	0.085	0.279	0	0	0	1
June	28,116	0.082	0.275	0	0	0	1
July	28,116	0.085	0.279	0	0	0	1
August	28,116	0.085	0.279	0	0	0	1
September	28,116	0.082	0.275	0	0	0	1
October	28,116	0.085	0.279	0	0	0	1
November	28,116	0.082	0.275	0	0	0	1
December	28,116	0.085	0.279	0	0	0	1
Monday	28,116	0.143	0.350	0	0	0	1
Tuesday	28,116	0.143	0.350	0	0	0	1
Wednesday	28,116	0.143	0.350	0	0	0	1
Thursday	28,116	0.143	0.350	0	0	0	1
Friday	28,116	0.143	0.350	0	0	0	1
Saturday	28,116	0.143	0.350	0	0	0	1
Sunday	28,116	0.143	0.350	0	0	0	1
Holiday	28,116	0.061	0.240	0	0	0	1

Note: Month,day and area dummies are listed in specific names

3.2 Methodology

I use "Post Double Selection" or "Double-Lasso" method by Belloni et al. (2013) for the estimation.

3.2.1 Temperature Intervals

I created five temperature intervals based on 10°C difference. The main reason for that is to see the reaction of electricity consumption at different temperatures. Moreover, because there are few observations between -20°C and -32°C, I take the observations up to -10°C as one interval. According to the Figure 8, most of the observations are between 0°C and 20°C. They cover 79.75 % of data. On the other hand, interval 4 covers 14.80 % of data. Intervals 1 and 5 which involve extreme temperature regimes covers 1.92 % and 3.50 % percent respectively.

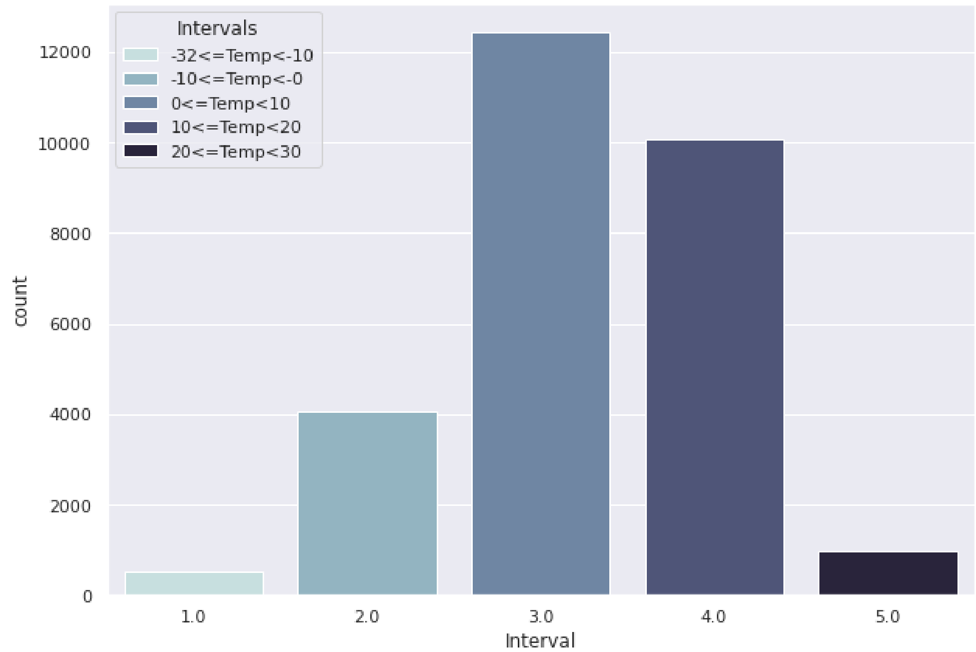

Figure 2: Temperature Intervals

3.2.2 Standardization

It is necessary to apply standardization before Lasso Regression used in Double Selection. James, Witten, Hastie, and Tibshirani (2013) stated that high variance variables tend to play a larger role in the principal components obtained in the absence of standardization. Hence, scale on which the variables are measured will ultimately have an effect on the model. Since Lasso Regression places a penalty on the magnitude of the coefficients, not standardizing can cause certain variables to dominate Lasso. Because of these reasons, I use standardized the data.

3.2.3 Post Double Selection/ Double-Lasso for Treatment and Causal Parameters

This study aims to analyze causal relationship between temperature increase and electricity consumption, so it is interested in average treatment effect. Since there are a lot of factors affecting the supposed cause and effect, data-adaptive procedures to select the variables to adjust for become increasingly necessary Kreif and DiazOrdaz (2019). Including too many regressors leads to overfitting whereas including too few regressors leads to omitted variable bias. Belloni et al. (2013) proposed a method which presents principled variable selection. It takes into account both confounder-outcome and confounder-treatment association, resulting in valid inferences after variable selection. There are three steps in this method;

1. Predict electricity consumption from set of confounders using lasso and collect the selected variables

2. Predict temperature from set of confounders using lasso and collect the selected variables

3. Regress temperature and selected variables by lasso on electricity consumption using OLS and get overall expected effect

3.2.3.1 Rigorous Lasso

I use Rigorous Lasso Regression for prediction steps of Post Double Selection procedure. Lasso Regression is a type of linear regression which uses shrinkage to choose best subset of variables by shrinking some of them towards zero (James et al. (2013)). Lasso Regression performs L1 Regularization that adds penalty term, λ which controls the strength of penalty, to the absolute value of the magnitude of coefficients. Larger penalties result in fewer coefficients, hence simpler models. The main goal of algorithm is to minimize :

$$\sum_{i=1}^{n}(y_i - (\beta_0 + \sum_{j}^{p} x_{ij}\beta_j))^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{1}$$

Equation 1 shows Residual Sum of Squares plus L1 Regularization. In the regularization part, lambda represents the amount of shrinkage. If it is zero, no parameters are eliminated. In contrast, more coefficients are eliminated with the increase in λ. The important point is the bias-variance trade-off. The increase in λ causes an increase in bias and decrease in variance. A high λ means that the flexibility of model is low, so bias is high. In order to choose optimal λ, rigorous lasso uses rigorous penaltization by Belloni, Chen, Chernozhukov, and Hansen (2012). It uses theory and data driven research by using feasible algorithms under heterosskedastic and non-Gaussian errors.

Step 1

Equation 2 represents the rigorous lasso regression equation of set of confounders on log electricity consumption.$log(y_i)$ represents the log consumption whereas z_i is the set of confounders. Besides, g_0 is a generic and non-linear function and μ_i is error term.

$$log(y_i) = \hat{g_0}(z_i) + \hat{\mu_i} \tag{2}$$

Step 2

In step 2, the only difference from Step 1 is the dependent variable. Equation 3 shows the rigorous lasso regression equation of set of confounders on temperature. $\d{i}$ represents the temperature whereas z_i is the set of confounders. Also, m_0 is generic and non-linear function whereas ν_i is the error term.

$$d_i = m_0(z_i) + \nu_i,\ E(\nu_i|Z_i, d_i) \tag{3}$$

Step 3

Equation 4 is the ordinary least squares regression of temperature and set of confounders selected in both step 1 and 2 on log electricity consumption. x_i represents the set of selected confounders by rigorous lassos and parameter β_{0i} is the expected effect. Since there are 5 temperature intervals, I apply step 3 for each temperature interval. Therefore, I obtain expected effect,β_{0i} for overall and 5 temperature intervals. β_{00} represents the overall effect whereas β_{01} to β_{05} are the expected effect on interval 1 to 5.

$$log(y_i) = \beta_{0i}d_i + g_0(x_i) + \mu_i,\ \ E(_i|Z_i),\ \ i\epsilon[0, 5] \tag{4}$$

4 Results

4.1 Selected Variables

Rigorous Lasso in step 1 and 2 selects variables from the set,z_i by variable selection. It identifies the variables that are strongly associated with the response variable. However, since the final step is about causation, different problems might arise. Multicollinearity is one of them. As variables Aarhus and Kopenhagen are strongly correlated with other variables. I exclude them from the set and do variable selection. The selected variables are ;

Oslo, Stavanger, Tromso, Bergen, Lulea, Stockholm, Jonkopings, Malmo, Helsinki, January, February, March, April,May, July, August, September, October, November, December, Monday, Tuesday, Thursday, Saturday, Sunday ,Holiday

Although these variables are included in OLS regression for overall effect and interval 3-4, collinearity problem arises for interval 1,2 and 5. Therefore, again, I exclude some variables from the set, x_i to overcome this problem. All VIF values are presented in Appendix. (See Table 5,6,7,8,9,10)

4.2 Findings

Table 3 illustrates the OLS regression results of step 3 in Post-Double Selection for both overall and interval effects. The results are in line with Bessec and Fouquau (2008) in general. Since PSTR parameters cannot be directly interpreted as elasticities, we can only say that sign of temperature parameter of Bessec and Fouquau (2008) is same which is negative as expected. My results suggest that 1°C temperature increase decreases electricity consumption by 2.3%. Besides, Bessec and Fouquau (2008) suggests that when the temperature rises, the effect becomes less and less negative, then it turns to positive. However, my results conflict with this argument. The reason is that they look at the relationship between temperature rise and electricity consumption with one transition function. In other words, they analyze the effect in the cold and warm regime, whereas I analyze the effect on different intervals of the cold and warm regime. This approach provides a more detailed analysis.

In a cold regime, results suggest that 1°C temperature increase decreases electricity consumption by 0.5% between -32°C and -10°C. The negative effect increases to 3.5% and 3.7% on intervals 2 (-10°C - 0°C) and 3 (0°C -10°C) respectively. The main reason for that is the diminishing heating effect. Households and buildings use electricity for heating less through the temperature intervals and it disappears after switching to warm regime. Bessec and Fouquau (2008) finds the threshold value for regime switching for cold countries as 14.7°C. Since I do not use a mechanism as Bessec and Fouquau (2008) , I can say that it is between 10°C-15°C, according to the Figure 1. Although the inflexion point representing the regime change is evident for some areas, it is not for others. In addition, the decrease in size of the effect on interval 4 (10°C-20°C) supports this argument. The negative effect of 1°C temperature rise on electricity consumption drops from -3.7% to -1.9%. The disappearance of diminishing heating effect might cause to this decrease. Because people use electricity for heating more between 0°C and 10°C than between 10°C and 20°C, the drop in usage of electricity for heating affects the negative effect of temperature rise on electricity consumption more. On the other hand, the effect of temperature increase turns to positive between 20°C and 30°C. 1°C increase in temperature increases electricity consumption by 1.2%. The emergence of cooling effect might trigger this change.Patronene Jenni et al. (2017) indicated that district cooling market is growing despite the cold climate.

Table 3: Regression Results

	Dependent variable:					
	log(Consumption)					
	Overall	Interval 1[-32°C,-10°C]	Interval 2[-10°C,0°C]	Interval 3[0°C,10°C]	Interval 4[10°C,20°C]	Interval 5[20°C,30°C]
Temp	−0.023***	−0.005***	−0.035***	−0.037***	−0.019***	0.012*
	(0.0004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.006)
$Temp_{Range}$	−0.002***	−0.001	0.003	−0.007***	0.0005	0.004
	(0.0005)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
Oslo	−0.049***	−0.570***	0.051***	0.012	−0.027***	−0.082***
	(0.006)	(0.013)	(0.018)	(0.010)	(0.010)	(0.032)
Stavanger	−0.022***	-	-	0.084***	−0.036***	−0.080*
	(0.006)			(0.009)	(0.010)	(0.043)
Tromso	−0.757***	−1.258***	−0.638***	−0.716***	−0.723***	−0.757***
	(0.006)	(0.019)	(0.016)	(0.010)	(0.013)	(0.089)
Bergen	−0.788***	-	-	−0.678***	−0.815***	−0.841***
	(0.006)			(0.009)	(0.010)	(0.054)
Lulea	−1.427***	−1.936***	−1.387***	−1.380***	−1.321***	−1.324***
	(0.006)	(0.008)	(0.017)	(0.011)	(0.011)	(0.043)
Stockholm	−0.873***	−1.371***	−0.794***	−0.829***	−0.808***	−0.846***
	(0.006)	(0.009)	(0.017)	(0.010)	(0.011)	(0.045)
Jonkopings	0.871***	0.431***	1.012***	0.943***	0.871***	0.750***
	(0.006)	(0.019)	(0.021)	(0.009)	(0.010)	(0.030)
Malmö	−0.377***	-	-	−0.278***	−0.390***	−0.487***
	(0.007)			(0.010)	(0.010)	(0.032)
January	−0.0004	0.029***	−0.055***	−0.059***	−0.298***	-
	(0.010)	(0.007)	(0.015)	(0.019)	(0.047)	
February	0.005	-	-	−0.062***	−0.349***	-
	(0.010)			(0.019)	(0.066)	
July	0.011	-	-	−0.016	−0.014*	−0.074***
	(0.008)			(0.038)	(0.008)	(0.028)
August	0.021***	-	-	0.027	0.017**	−0.033
	(0.008)			(0.031)	(0.008)	(0.032)
September	−0.001	-	-	0.052***	0.012	−0.019
	(0.008)			(0.020)	(0.008)	(0.093)
October	−0.013	-	-	0.008	−0.021*	-
	(0.008)			(0.018)	(0.012)	

November	0.005	−0.041***	0.036**	−0.017	−0.087***	-
	(0.009)	(0.015)	(0.018)	(0.018)	(0.024)	
December	0.006	−0.025***	0.054***	−0.038**	−0.199***	−0.345***
	(0.009)	(0.009)	(0.016)	(0.018)	(0.041)	(0.110)
Monday	−0.001	−0.007	−0.005	−0.004	0.001	0.029
	(0.005)	(0.008)	(0.017)	(0.007)	(0.008)	(0.029)
Tuesday	0.006	−0.005	0.012	0.001	0.007	0.023
	(0.005)	(0.009)	(0.017)	(0.007)	(0.008)	(0.028)
Thursday	0.006	−0.0004	−0.001	0.006	0.006	-
	(0.005)	(0.008)	(0.017)	(0.007)	(0.008)	
Holiday	−0.036***	−0.044***	−0.0001	−0.043***	−0.031**	−0.049
	(0.007)	(0.013)	(0.023)	(0.009)	(0.013)	(0.073)
Saturday	−0.079***	−0.052***	−0.063***	−0.073***	−0.094***	−0.088***
	(0.005)	(0.009)	(0.017)	(0.008)	(0.008)	(0.027)
Sunday	−0.091***	−0.054***	−0.069***	−0.088***	−0.103***	−0.097***
	(0.005)	(0.008)	(0.017)	(0.008)	(0.008)	(0.028)
April	−0.033***	-	-	−0.026	−0.045***	-
	(0.008)			(0.018)	(0.016)	
May	−0.026***	-	-	−0.034*	0.006	0.051
	(0.008)			(0.018)	(0.009)	(0.046)
Helsinki	−0.956***	-	-	−0.922***	−0.894***	−0.920***
	(0.006)			(0.010)	(0.009)	(0.030)
March	−0.017*	−0.038***	−0.036**	−0.058***	−0.031	-
	(0.009)	(0.010)	(0.016)	(0.018)	(0.082)	
Constant	11.720***	12.309***	11.537***	11.782***	11.616***	11.079***
	(0.010)	(0.016)	(0.019)	(0.021)	(0.021)	(0.138)
Observations	27,123	520	4,001	11,940	9,717	945
R^2	0.857	0.994	0.790	0.852	0.849	0.822
Adjusted R^2	0.856	0.994	0.789	0.852	0.849	0.818
Res. Std.Err	0.252 (df = 27094)	0.058 (df = 502)	0.330 (df = 3983)	0.252 (df = 11911)	0.244 (df = 9688)	0.276 (df = 923)
F Stat.	5,775.692*** (df = 28; 27094)	4,816.226*** (df = 17; 502)	881.244*** (df = 17; 3983)	2,451.895*** (df = 28; 11911)	1,950.778*** (df = 28; 9688)	203.390*** (df = 21; 923)

*p<0.1; **p<0.05; ***p<0.01

5 Discussion and Conclusion

In this study, I analyze the casual impact of temperature increase as a consequence of climate change on electricity consumption by using Post Double Selection method by Belloni et al. (2013).

I use daily electricity consumption data from Nord Pool and daily average temperature data from methodological institutes of Nordic countries. I create 5 temperature intervals instead of using HDD and CDD or transition functions like most of the other studies to capture the relationship at different temperature intervals. By doing this, I obtain more detailed results than Bessec and Fouquau (2008). Since most of the studies' results differ, results of this study both suits and conflicts with some of older studies. However, it is not feasible to compare results as timeline differs. A comment can be made about the difference between decades. For example, Bessec and Fouquau (2008) and Eni et al. (2007) find negative effect for cold countries before the year 2000 whereas I find stronger negative effect between 2013 and 2019. This means that there is an increasing effect of global warming on electricity consumption through decades.

As with any research, this research has also limitations. One limitation is the missing regional data for Finland. As Finland is a big country, having more regional data for consumption helps results to be more accurate. On the other hand, another limitation is deficiency of macroeconomic variables such as GDP and population data. This study does not use monthly data like Bessec and Fouquau (2008) because it is not possible to disaggregate yearly data into daily data. Therefore,there must be an assumption that population and GDP are fixed over time to say that findings is valid in future.

For policy recommendations, Nordic governments should take some actions. It should be noted that Nordic electricity production is two-thirds renewable. Since each country does not specialize in one electricity resource, actions must differ. In general, hydro power takes an important place in electricity production for all Nordic countries except Denmark.It is likely that climate change will alter river discharge, resulting in impacts on water availability, water regularity, and hydropower generation Berga (2016). In addition, hydropower potential is expected to increase 15% to 30% for Northern and Eastern Europe. Results of the study shows that electricity consumption decreases by 2.3% when temperature increases by 1%. According to NASA, 1 global temperature increase is expected in 50 years. Therefore,hydropower potential will increase whereas electricity consumption will decrease compared to today. Considering hydropower is the only system that currently exists to store energy in a significant and effective way, in the form of pumped storage power plants Fairley (2015), governments should increase investing in hydropower plants for capacity increase. On the other hand, same scenario applies to Denmark. There is evidence for increased wind energy resources by the end of the current century in northern Europe and the US Southern Great Plains Pryor, Barthelmie, Bukovsky, Leung, and Sakaguchi (2020). Hence, Danish government should go through capacity planning on wind turbines for the future to balance the energy consumption. Lastly, from my point of view, Finland and Sweden should reduce the usage amount of Nuclear energy as it is so expensive and dangerous. They can increase the usage of hydropower in electricity production to be more efficient and less risky.

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7 Appendix

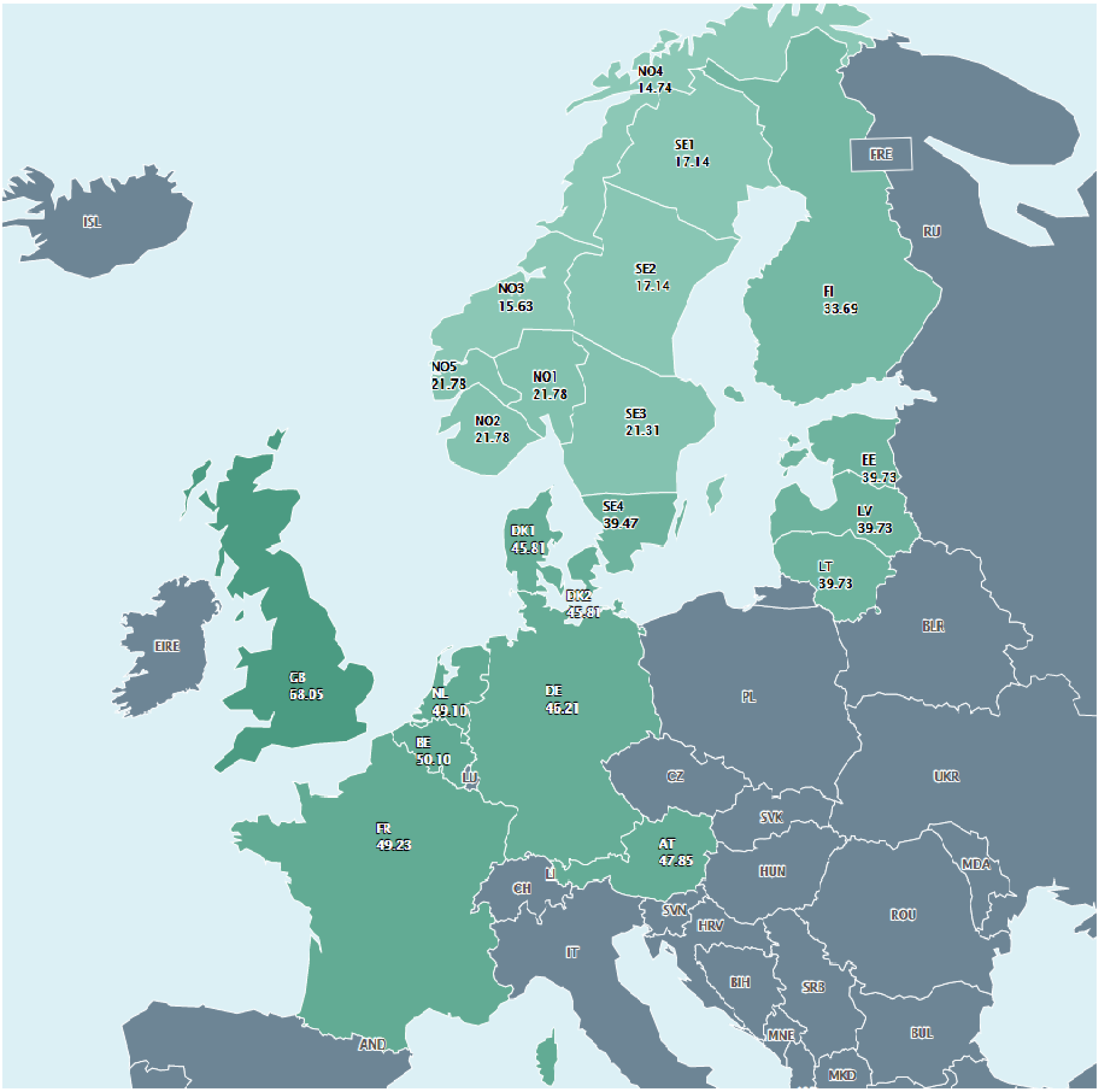

Figure 3: Nord Pool Market Map, from Nord Pool AS (n.d.)

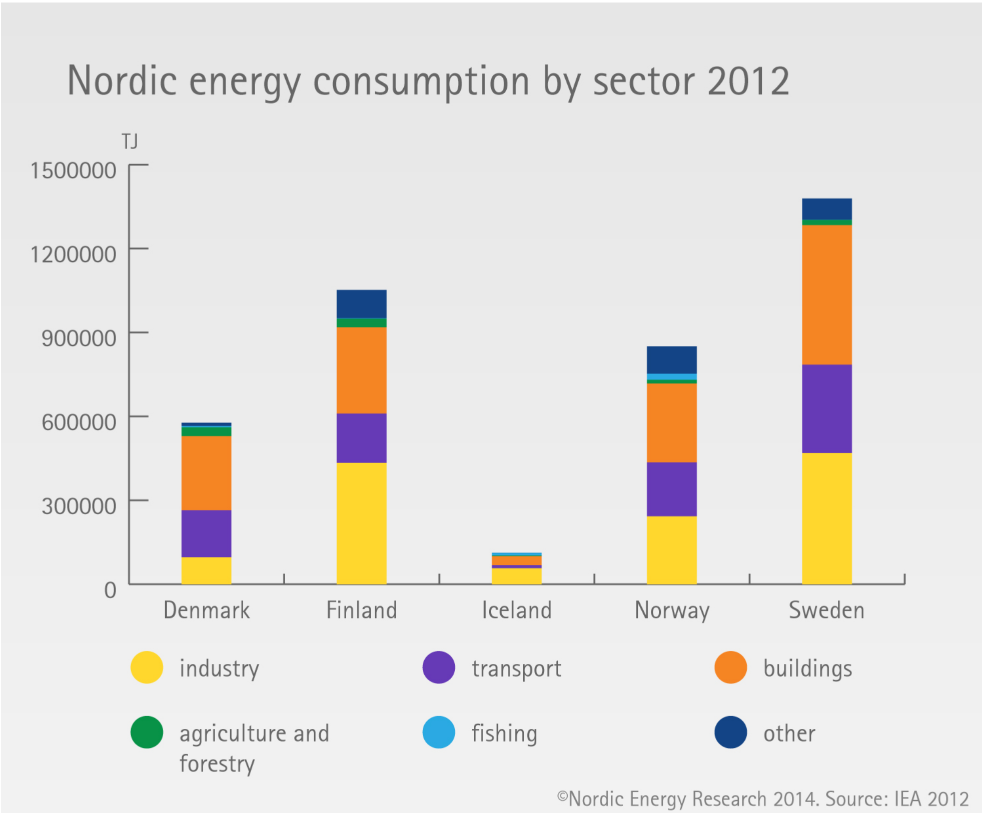

Figure 4: Nordic Energy Consumption by Sector in 2012, from Nordic Energy Research (2012)

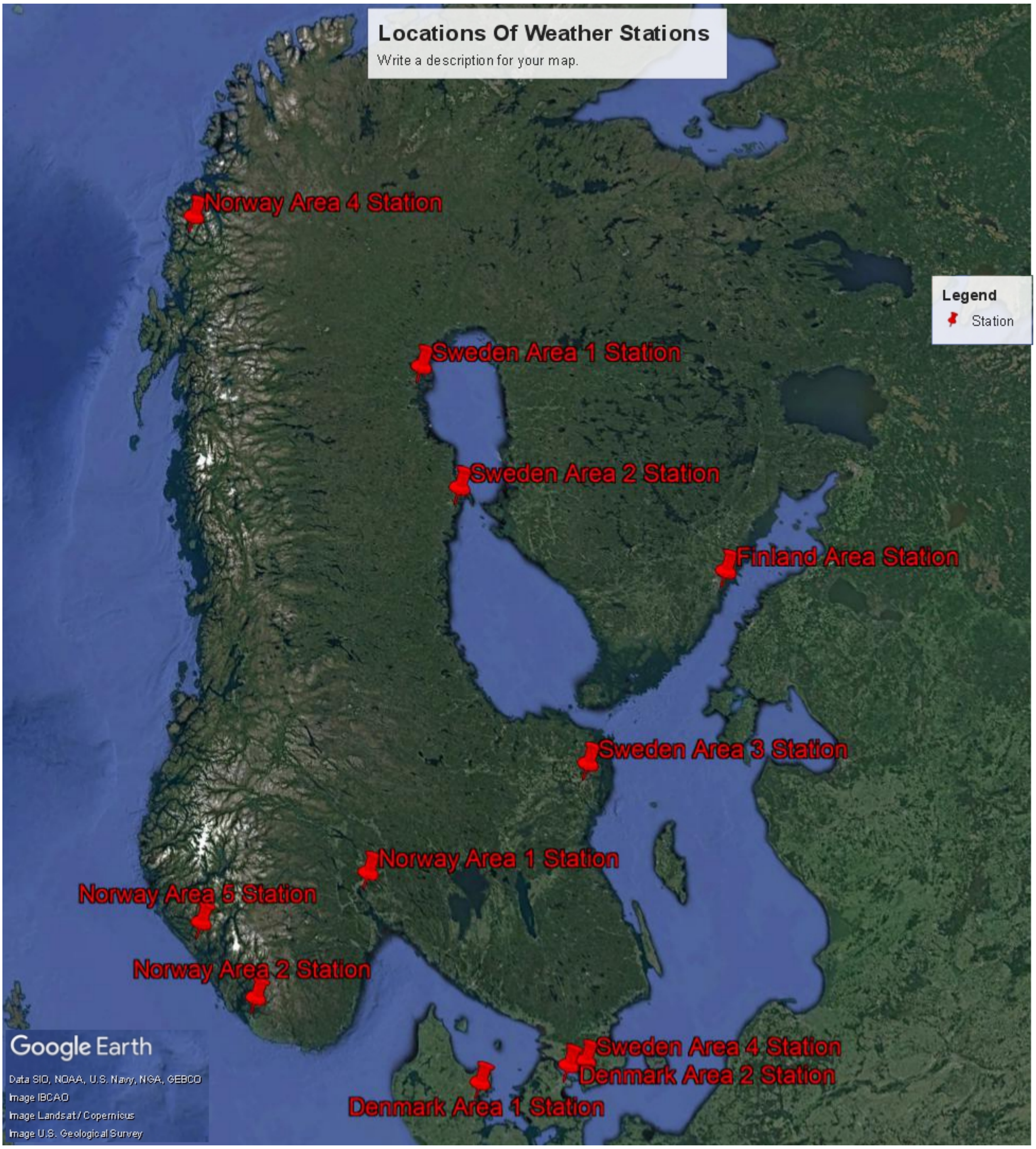

Figure 5: Weather Stations' Locations, from *Google Earth Nordic Map* (2020)

Table 4: Descriptive Statistics
(No:Norway,Sw:Sweden,Den:Denmark,Fin:Finland)

Name	n	Min	q_1	$\tilde{x}$	$\bar{x}$	q_3	Max	s	IQR	#NA
Oslo-Temperature	2556	-14.0	1.3	6.8	7.5	14.4	28.0	7.9	13.1	0
Stavanger-Temperature(	2556	-8.8	4.8	8.4	8.7	13.1	27.8	5.5	8.3	0
Tromso-Temperature	2556	-15.4	-1.1	3.2	3.8	9.0	24.7	6.5	10.1	0
Bergen-Temperature	2556	-9.6	4.0	7.7	8.1	12.4	25.2	5.5	8.4	0
Lulea-Temperature	2556	-31.1	-2.9	3.0	3.3	11.8	25.6	9.9	14.7	0
Stockholm-Temperature	2556	-24.1	-1.1	3.9	4.4	12.2	25.1	8.8	13.3	0
Jonkopings-Temperature	2556	-14.1	2.3	7.7	8.4	15.0	26.9	7.7	12.7	0
Malmö-Temperature	2556	-11.2	4.3	9.5	9.7	15.6	26.4	6.8	11.3	0
Aarhus-Temperature	2556	-9.2	4.1	8.8	8.9	14.0	23.6	6.1	9.8	0
Kopenhagen-Temperature	2334	-7.4	5.0	10.3	10.3	16.0	25.5	6.6	11.1	222
Helsinki-Temperature	2556	-25.0	0.5	5.8	6.6	14.3	26.4	8.8	13.8	0
Oslo-Consumption	2556	49218.0	71293.8	95578.0	98802.6	124610.2	183001.0	30370.4	53316.5	0
Stavanger-Consumption	2556	67306.0	80881.8	94530.5	96233.7	110169.8	145511.0	16869.4	29288.0	0
Tromso-Consumption	2556	30122.0	44519.5	51701.0	51679.5	58617.0	70290.0	8451.7	14097.5	0
Bergen-Consumption	2556	25055.0	37712.2	45245.0	45590.7	52556.8	74379.0	8862.1	14844.5	0
Lulea-Consumption	2556	17583.0	22949.0	25972.5	26573.5	29750.8	55951.0	4401.1	6801.8	0
Stockholm Consumption	2556	29491.0	38299.8	44249.5	45331.0	51375.8	87438.0	8198.2	13076.0	0
Jonkopings-Consumption	2556	149653.0	200718.0	231008.0	236571.0	273567.0	379797.0	46901.7	72849.0	0
Malmö-Consumption	2556	41170.0	55860.0	63631.5	65919.9	76542.8	106889.0	13552.2	20682.8	0
Aaarhus-Consumption	2556	37558.0	49317.0	55011.0	54398.3	58972.8	71498.0	6604.1	9655.8	0
Kopenhagen-Consumption	2556	27126.0	33227.8	35612.5	36230.3	39327.2	48542.0	4266.7	6099.5	0
Helsinki-Consumption	2556	107837.0	150874.0	177355.5	177880.8	201683.8	261282.0	31623.8	50809.8	0

Note : temperature is measured in °C and consumption is measured in MW (Megawatt)

Figure 6: Lasso Graphs for Step 1 and Step 2

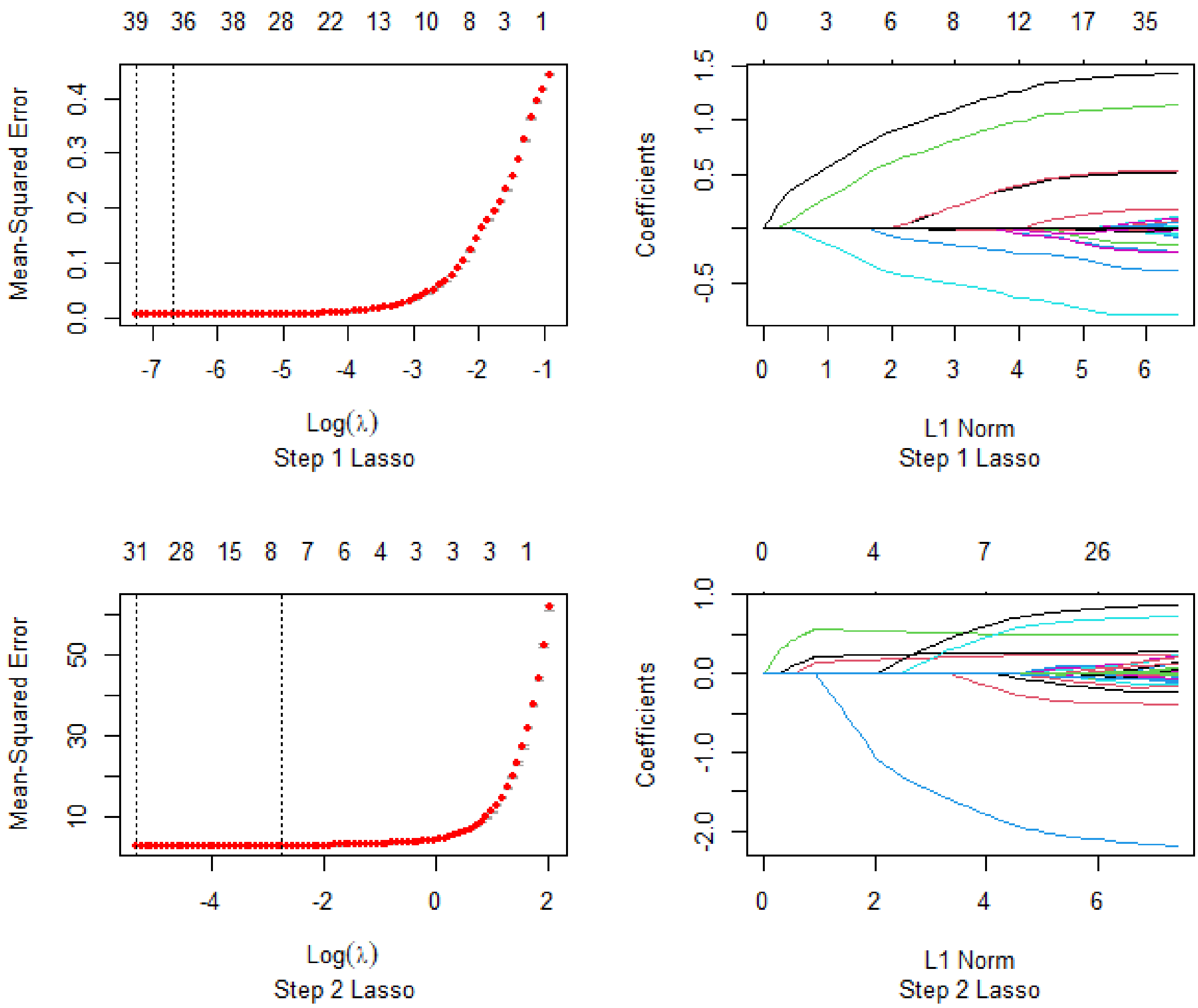

Table 5: VIF Values of OLS Regression for Overall

d	4.040
Diff	1.445
Norway_A1	1.365
Norway_A2	1.383
Norway_A4	1.512
Norway_A5	1.371
Sweden_A1	1.508
Sweden_A2	1.458
Sweden_A3	1.368
Sweden_A4	1.274
January	3.309
February	2.903
July	1.910
August	1.888
September	1.882
October	2.202
November	2.571
December	2.784
Monday	1.287
Tuesday	1.286
Thursday	1.286
Holiday	1.106
Saturday	1.287
Sunday	1.286
April	2.246
May	1.923
Finland_A	1.349
March	2.767

Table 6: VIF Values of OLS Regression for Interval 1

d	1.217
Diff	1.458
Norway_A1	1.361
Norway_A4	1.181
Sweden_A1	2.425
Sweden_A2	2.411
Sweden_A3	1.194
January	1.713
November	1.176
December	1.427
Monday	1.340
Thursday	1.348
Holiday	1.072
Saturday	1.301
Sunday	1.324
March	1.413
Tuesday	1.304

Table 7: VIF Values of OLS Regression for Interval 2

d	1.149
Diff	1.263
Norway_A1	1.269
Norway_A4	1.435
Sweden_A1	1.473
Sweden_A2	1.436
Sweden_A3	1.192
January	1.486
November	1.268
December	1.322
Monday	1.306
Thursday	1.284
Holiday	1.048
Saturday	1.311
Sunday	1.313
March	1.378
Tuesday	1.308

Table 8: VIF Values of OLS Regression for Interval 3

d	1.626
Diff	1.423
Norway_A1	1.363
Norway_A2	1.487
Norway_A4	1.741
Norway_A5	1.473
Sweden_A1	1.405
Sweden_A2	1.420
Sweden_A3	1.391
Sweden_A4	1.320
January	5.581
February	5.853
July	1.215
August	1.347
September	2.686
October	6.375
November	7.166
December	7.134
Monday	1.276
Tuesday	1.282
Thursday	1.280
Holiday	1.100
Saturday	1.276
Sunday	1.273
April	7.318
Finland_A	1.365
March	6.922
May	4.740

Table 9: VIF Values of OLS Regression for Interval 4

d	1.578
Diff	1.335
Norway_A1	1.343
Norway_A2	1.442
Norway_A4	1.310
Norway_A5	1.439
Sweden_A1	1.344
Sweden_A2	1.348
Sweden_A3	1.362
Sweden_A4	1.286
January	1.034
February	1.019
July	1.707
August	1.770
September	1.705
October	1.513
November	1.104
December	1.034
Monday	1.297
Tuesday	1.288
Thursday	1.294
Holiday	1.106
Saturday	1.295
Sunday	1.295
April	1.209
Finland_A	1.394
March	1.009
May	1.518

Table 10: VIF Values of OLS Regression for Interval 5

d	1.113
Diff	1.457
Norway_A1	1.281
Norway_A2	1.184
Norway_A4	1.033
Norway_A5	1.086
Sweden_A1	1.165
Sweden_A2	1.139
Sweden_A3	1.428
Sweden_A4	1.260
July	2.371
December	1.106
Monday	1.153
Tuesday	1.149
Holiday	1.104
Saturday	1.151
Sunday	1.153
May	1.327
Finland_A	1.413
August	2.137
September	1.117