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Ambient air pollution and meteorological factors escalate electricity consumption

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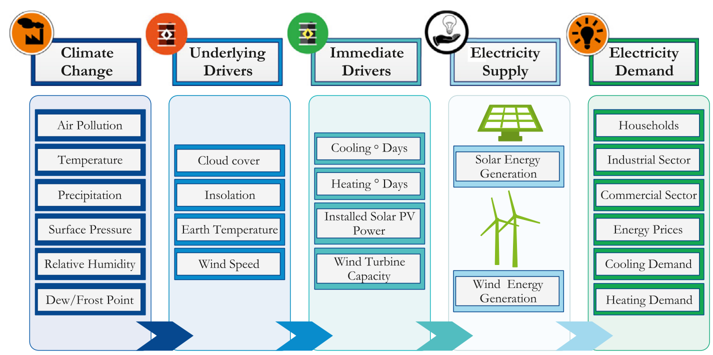
HIGHLIGHTS

- We examine the role of climatic and energy-related effects on electricity consumption.
- The novel Kernel Regularized Least Squares (KRLS) estimator is used in this study.
- Wind speed declines solar, households and commercial electricity consumption.
- Heating degree days spur household and commercial electricity consumption.
- Precipitation intensity improves solar resources by increasing surfaces of solar PV.

GRAPHICAL ABSTRACT



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ABSTRACT

The impact of climate change is evident in the variability of weather patterns, hence, affecting electricity generation and consumption. Existing literature examines the effect of humidity and temperature on energy, but suffers from omitted variable bias. Here, we adopt several parameters namely ambient air pollution, precipitation, surface pressure, dew-frost point, relative humidity, wind speed, earth skin temperature, cooling degree days, heating degree days, solar and wind generation, cumulative installed PV power, and wind turbine capacity, solar and wind electricity consumption, and energy price index to investigate the role of climatic and energy-related factors on households, industry sector, commercial and public service attributed electricity consumption in Norway. Our machine learning estimator accounts for climate change heterogeneity, and historical effects while controlling omitted-variable and misspecification bias. The empirical assessment shows the radiative forcing effect of ambient air pollution decreases electricity consumption. In contrast, the scavenging effect of rainfall intensity on ambient air pollution improves both wind and solar electricity consumption. Rising levels of earth skin temperature, and humidity increases solar and wind electricity consumption whereas dew-frost point drops temperature, and humidity to improve human comfort. Our study highlights that energy price index is critical to the adoption of solar and wind energy technologies.

1. Introduction

Climate change and its impact have become a global phenomenon–– with its environmental changes observed over decades. Drivers of climate change cannot be explained without the role of anthropogenic

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greenhouse gas (GHG) emissions. The combustion of oil, coal, and natural gas releases carbon dioxide––which predominantly drives anthropogenic GHG emissions by increasing atmospheric concentration that impacts future global climate conditions (Blanco et al., 2014). GHG emissions became the focal point at the global scale during the Kyoto protocol in 1997, and Paris agreement adopted by 196 parties in December 2015 and effected in November 2016. The main objective of the Paris agreement required signatory countries to reduce GHG emissions––to control the rise in global temperature below 2 degrees Celsius (Rogelj et al., 2019). However, energy requirements to satisfy societal needs and facilitate economic development cannot be overemphasized. Hence, electricity consumption has historically increased due to economic growth, population dynamics, and modernization of society (Owusu and Asumadu, 2016).

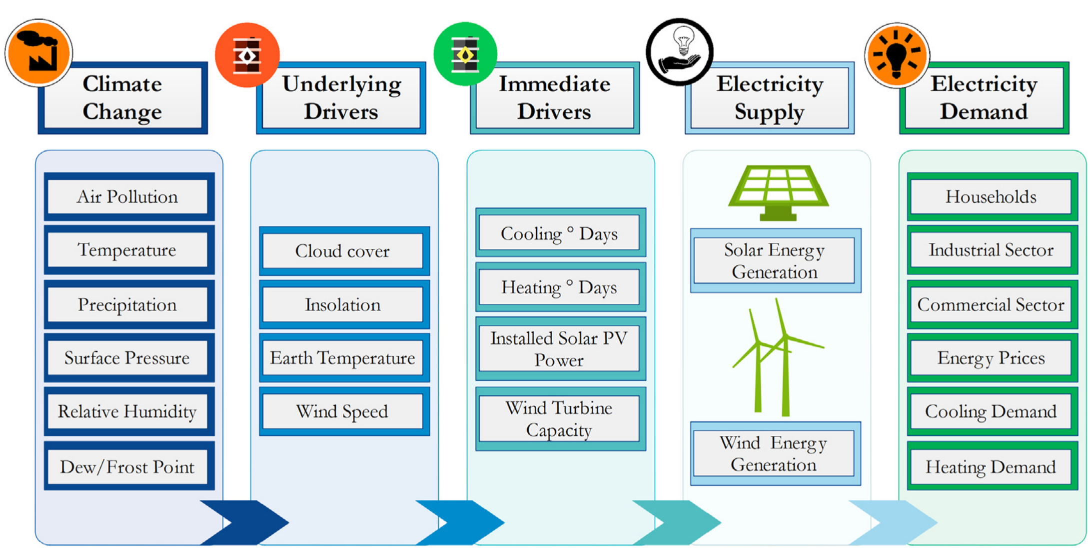
The challenges of climate change do not hinder the spirit of Norwegian people––as they pride themselves in the belief that––there is no such thing as bad weather, be it cold or rainy but only bad clothes. However, Norway has the highest renewable energy source and lowest emissions from the power sector across Europe––accounting for 98% of the total electricity supply. The most important characteristic of renewable energy is the ability to generate minimal or no GHG emissions. As of 2018, the normal annual electricity production was 141-terawatt hour (TWh)––a large investment was made in renewable energy production capacity than decades ago. Energy consumption in Norwegian households varies from 72% to 79% since the last 20 years. Hydro energy constitutes the major source of renewable energy, contributing about 96% of the total electricity production in Norway. However, there is a huge potential for wind energy because of its long and windy coastal areas throughout the country––although contributing to a relatively moderate share of power production capacity. Norwegian onshore wind power plants consist of installed capacity of 1695 MW for annual production of 5.3 TWh [est. 2018] (MOPE, 2021). This aligns with European zone's target to reduce GHG emissions by increasing the share of renewable energy from 8.5% in 2005 to 20% in 2020 (EU, 2009). Global power production is estimated to reach 46% of world renewable energy production capacity by 2050 to mitigate the increasing levels of GHG emissions (IRENA, 2018).

Climate change poses great threats, owing to its adverse effects on the environment––and long-term implications on the reliability and performance of renewable energy systems (Scheme 1). While electricity demand is driven by climate change, electricity supply affects climate change through its generation process. The supply of renewable energy source such as hydro, wind, and solar is disrupted by climatic factors including air pollution, precipitation, temperature, surface pressure, relative temperature, and frost point in varying degrees––through the underlining drivers of wind speed, cloud cover, insolation, and earth temperature. The photovoltaic (PV) performance can reduce the reliability of solar panels due to the emission of aerosols. The emission of aerosols can reduce solar electricity generation through a decline in solar radiation by scattering and absorbing solar energy (He et al., 2020). Besides, severe air pollution experience can reduce the average PV generation capacity by 11–15% (Sweerts et al., 2019).

In colder regions like Norway, large snow particles can settle on PV modules, rendering them inefficient. The renewable energy source resilient infrastructure and reliability can be affected by extreme climate change through storm damages to coastal transmission lines and strategic infrastructure settings. The changes in climatic conditions may affect the supply of renewable energy sources through their impact on land used for cultivating bioenergy and competition with food production (Yalew et al., 2020). This will hamper efforts to decarbonize the energy sector, as the unreliability of renewable energy sources may result in intensified use of fossil fuels or reinforce infrastructure (Godzimirski, 2014).

The demand pattern of electricity is changing at alarming rate due to increasing temperature attributed to climate change (Magazzino et al., 2021). This affects the duration and magnitude of seasonal heating and cooling required. Norway is characterized by cooled and long climatic conditions that require heating with an annual usage of 80 terawatt hour (TWh) in both private and commercial buildings––where an estimate of 50% is used for heating (Rosenberg and Espegren, 2009). The weather condition in Norway is predominately cold, so less energy is used for cooling. Traditionally, the cost of electricity is less expensive but electricity is used more for heating in both private and commercial buildings. Climate change impacts may also be experienced in the form of cross-sectional resource competitions––where water is required for hydro energy generation, cooling thermal plants, and for other uses including irrigation, ecosystem, manufacturing, and domestic water supply. Notably, Norway's climate conditions are highly dependent on heat transported from the North Atlantic Ocean current, however, a significant reduction in this heat current has been observed in the past decades (Houghton, 2001). Weakening of ocean currents may result in unstable climatic conditions in Norway, which may lead to possible feedback of negative temperature changes (Vellinga and Wood, 2002).

It is therefore imperative for researchers and institutions to ascertain the effects of climate change on electricity demand and supply. The



Scheme 1. Conceptualization of the nexus between ambient air pollution, meteorological factors and electricity consumption.

adaptation of renewable energy systems to climate change can reduce the vulnerability through the mixture of electricity and technologies such as—less power consumption devices, alternative methods of cooling thermal plants to reduce water usage, and reduction in power demand (Ebinger and Vergara, 2011). Numerous research projects in the last decades analyzed the impact of climate change on energy production, especially renewable energy sources. The US energy system review indicates 1 °C temperature will change energy consumption within the range of 5% (Wilbanks et al., 2008). These studies also report the effect of climate change on electricity demand in Australia and New Zealand. For example, findings indicate 1 °C winter temperature reduces electricity demand within the range of 3% (Beyene et al., 2010; Blendon et al., 2008). However, literature on the scope is limited in Norway. The only existing study examined the effect of climate change on Norwegian energy production system toward achieving the 2050 target by employing MARKAL Norwegian model using data from Norwegian meteorological agency (Seljom et al., 2011).

Recent literature presents direct effect of climate change on electricity demand, ignoring indirect drivers and electricity supply dynamics that hamper both production and consumption. Both indirect drivers and electricity supply dynamics have long-term impact on energy prices, and sectoral demand. Thus, failure to accurately account for these intermediaries and environmental externalities of climate change thwarts efforts toward achieving environmental sustainability. In contrast to previous literature that suffers from omitted variable bias, we use country-specific meteorological and energy-related data––including air pollution, precipitation, surface pressure, dew/frost point, relative humidity, wind speed, earth skin temperature, cooling and heating degree days, solar and wind generation, cumulative installed photovoltaic power, installed wind turbine capacity, solar and wind electricity consumption, and energy price index––to analyze the impact of climate change on Norwegian households, industrial sector, commercial and public service attributed electricity consumption. We adopt novel estimation techniques that account for heterogeneous and historical effects of climate change while controlling omitted-variable and misspecification bias. A useful conclusion can be drawn from the study to formulate strategies for the development of public and investment policies on climate change and renewable energy capacity. The country-specific research highlights the differences in climate change exposure, and trends for policy implementation and strategies coupled with global climate change policies.

2. Methods

The conceptualization of the nexus between ambient air pollution, meteorological factors, and electricity consumption depicted in Scheme 1 was executed by the collation of data from multiple sources including NASA (2020), British Petroleum (2018), World Bank (2020), and OECD (2018). This study is based on empirical research that adopts econometric techniques based on time series data. The 21 set of variables presented in Table 1 (especially meteorological factors) is based on 0.5 × 0.5 degree inter-annual averages/sums for Norway with elevation from MERRA-2: average for ½ × ½ degree latitude/longitude region = 909.05 m spanning 1981–2019. The data series involve precipitation (PRECIP), cooling degree days (CDD), heating degree days (HDD), surface pressure (PS), dew/frost point (DEW), relative humidity (RHUM), wind speed (WSPEED), earth skin temperature (TS), solar generation (GENSOLAR), wind generation (GENWIND), cumulative installed photovoltaic power (INSTALPV), cumulative installed wind turbine capacity (INSTALWIND), solar electricity consumption (RESOLAR), wind electricity consumption (REWIND), electricity generation (ELEGEN), energy price index (ENPRICE), Particulate Matter 2.5 (PM2.5), final electricity consumption (FC), households electricity consumption (FC_{HH}), industrial sector electricity consumption (FC_{IND}), and commercial and public services electricity consumption (FC_{CP}). The trend of normalized data series used for empirical assessment is depicted in Chart 1. Long-term

Table 1
Variable selection and description.

Abbrev	Meaning	Unit
PRECIP	Precipitation	mm/day
CDD	Cooling degree days above 0 °C	°C-d
HDD	Heating degree days below 18.3 °C	°C-d
PS	Surface pressure	kPa
DEW	Dew/frost point at 2 meters	°C
RHUM	Relative humidity at 2 meters	%
WSPEED	Wind speed at 50 meters	m/s
TS	Earth skin temperature	°C
GENSOLAR	Renewables generation - solar	TWh
INSTALPV	Cumulative installed photovoltaic (PV) power	MW
RESOLAR	Renewables consumption - solar	Mtoe
GENWIND	Renewables generation - wind	TWh
REWIND	Renewables consumption - wind	Mtoe
INSTALWIND	Cumulative installed wind turbine capacity	MW
ELEGEN	Electricity generation	TWh
ENPRICE	Energy price index	real 2010 USD
PM2.5	Particulate Matter 2.5	$\mu g/m^3$
FC	Final consumption	GWh
FC_{HH}	Final consumption - households - energy use	GWh
FC_{IND}	Final consumption - industrial sector - energy use	GWh
FC_{CP}	Final consumption - commercial and public services - energy use	GWh

fluctuations are observed along the horizon among 15/21 sampled series whereas increasing trend is observed in 6/21 variables. These structural characteristics emphasize the variability and complexity of climatic factors, hence, require investigation using novel estimation techniques.

The characteristics of data series presented in Box 1 show an annual average of 4.21 m/s wind speed, −1.40 °C earth skin temperature, −2.35 °C dew/frost point, 88.06% relative humidity, 90.41 kPa surface pressure, 931.23 mm/day precipitation, 6968.79 °C-d heating degree days, and 1224 °C-d cooling degree days. Aside from meteorological conditions, we further observe the descriptive statistical analysis of pollutants and energy attributes comprising the mean distribution of 18.16 $\mu g/m^3$ Particulate Matter 2.5, 0.30 Mtoe wind electricity consumption, 0.004 Mtoe solar electricity consumption, 545.55 MW cumulative installed wind turbine capacity, 10.61 MW cumulative installed PV power, 1.39 TWh wind generation, 0.02 TWh solar generation, and US $ 61.55 energy price index. Besides, we further observe an average distribution consisting of 125.17 TWh electricity generation, 35,414 GWh final household electricity consumption, 22,908 GWh final commercial and public service electricity consumption, 46,883 GWh final industrial sector electricity consumption, and 111,038 GWh final electricity consumption. The Jarque-Bera test shows all variables are normal distributed excluding wind generation, solar generation, precipitation, cumulative installed wind turbine capacity, cumulative installed PV power, solar electricity consumption, and wind electricity consumption. The observations reveal unequal distribution of the annual frequency series underscoring the importance of estimation tools that can control for missing values.

2.1. Model specification

The model estimation of the conceptualized relationship begins with a linear function expressed as:

$$\ln FC_t = f(lnFC_{t-1}, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t) \quad (1)$$

$$lnRESOLAR_t = f(lnRESOLAR_{t-1}, lnGENSOLAR_t, TS_t, lnINSTALPV_t, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t) \quad (2)$$

$$lnREWIND_t = f(lnREWIND_{t-1}, TS_t, lnINSTALWIND_t, lnGENWIND_t, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t, DEW_t) \quad (3)$$

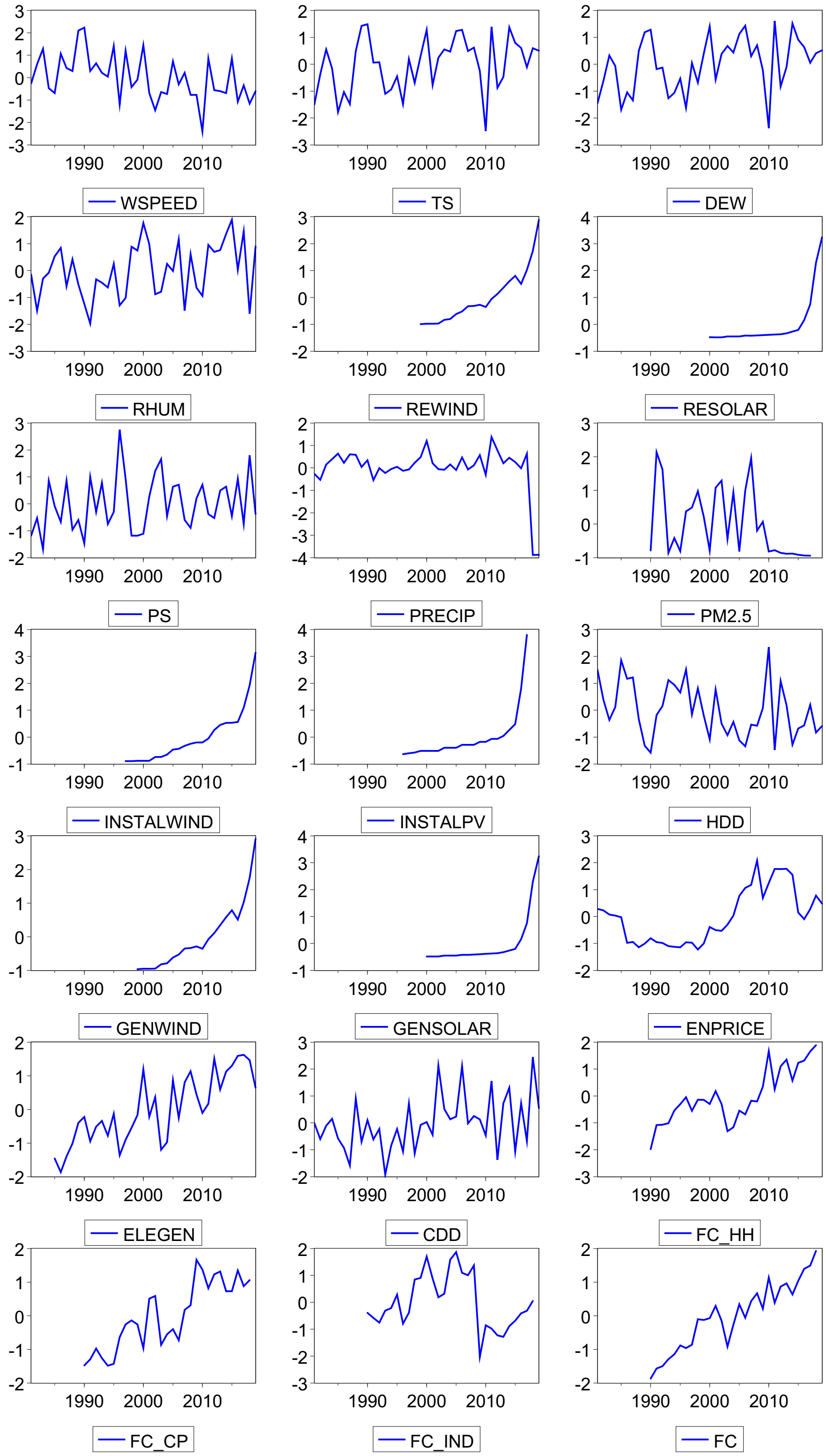


Chart 1. Trend of normalized data series used for empirical assessment.

$$lnFC_{HHt} = f(lnFC_{HHt-1}, TS_t, lnPS_t, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t, DEW_t, lnELEGEN_t) \tag{4}$$

$$lnFC_{INDt} = f(lnFC_{INDt-1}, TS_t, lnPS_t, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t, DEW_t) \tag{5}$$

$$lnFC_{CPt} = f(\ln FC_{CPt-1}, TS_t, lnPS_t, lnWSPEED_t, lnCDD_t, lnHDD_t, lnPM2.5_t, lnPRECIP_t, lnENPRICE_t, lnRHUM_t, DEW_t, lnELEGEN_t) \tag{6}$$

where *ln* is the log-transformation of data series, *lnFC*, *lnRESOLAR*, *lnREWIND*, $lnFC_{HH}$, $lnFC_{IND}$, and $lnFC_{CP}$ represent the target variables in time *t*, $lnFC_{t-1}$, $lnRESOLAR_{t-1}$, $lnREWIND_{t-1}$, $lnFC_{HHt-1}$, $lnFC_{INDt-1}$, and

Box 1
Descriptive statistical analysis of sampled series.
Legend: The green check mark denotes failure to reject the null hypothesis of normal distribution whereas red cross mark represents the null hypothesis at *p-value* < 0.05.

Statistics	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob>0.05	Obs
WSPEED (m/s)	4.210	4.150	4.730	3.650	0.233	0.230	2.845	0.384	✓	39
TS (°C)	-1.401	-1.230	-0.100	-3.580	0.877	-0.438	2.502	1.648	✓	39
DEW (°C)	-2.352	-2.310	-1.160	-4.120	0.742	-0.355	2.409	1.384	✓	39
RHUM (%)	88.061	88.050	89.450	86.610	0.736	-0.050	2.081	1.389	✓	39
REWIND (Mtoe)	0.304	0.207	1.179	0.003	0.303	1.321	4.449	7.940	✗	21
RESOLAR (Mtoe)	0.004	0.002	0.024	0.001	0.006	2.446	7.669	38.113	✗	20
PS (kPa)	90.412	90.370	90.790	90.180	0.137	0.551	2.856	2.005	✓	39
PRECIP (mm/day)	931.229	967.140	1262.210	2.510	239.443	-2.946	12.408	200.222	✗	39
PM2.5 (μg/m^3)	18.164	13.073	43.399	7.046	11.811	0.737	2.167	3.342	✓	28
INSTALWIND (MW)	545.548	395.000	2444.300	5.000	604.746	1.635	5.542	16.440	✗	23
INSTALPV (MW)	10.614	8.000	45.000	4.900	9.039	2.908	11.027	90.072	✗	22
HDD (°C-d)	6968.786	6917.040	7631.060	6523.290	282.281	0.399	2.329	1.765	✓	39
GENWIND (TWh)	1.392	0.913	5.538	0.014	1.425	1.372	4.574	8.754	✗	21
GENSOLAR (TWh)	0.019	0.008	0.113	0.005	0.029	2.446	7.676	38.161	✗	20
ENPRICE (US$)	61.551	60.664	125.565	23.781	30.771	0.522	2.084	3.133	✓	39
ELEGEN (TWh)	125.167	122.660	149.402	97.284	14.941	0.069	1.898	1.798	✓	35
CDD (°C-d)	1224	1222	1548	970	132	0.565	3.139	2.107	✓	39
FC_HH (GWh)	35414	34948	40299	30299	2587	0.295	2.315	0.988	✓	29
FC_CP (GWh)	22908	22583	26892	19353	2393	0.011	1.666	2.150	✓	29
FC_IND (GWh)	46883	46027	52025	41289	2753	0.222	2.216	0.980	✓	29
FC (GWh)	111038	110603	125125	97373	7313	-0.088	2.141	0.929	✓	29

$lnFC_{CPt-1}$ are the lagged-dependent variables––used to control omitted-variable bias and account for historical effects.

The bivariate model specification used to examine the nexus between wind electricity consumption vs. cumulative installed wind turbine capacity and wind electricity generation can be expressed as:

$$lnREWIND_t = lnINSTALWIND_t + lnINSTALWIND_t^2 + lnINSTALWIND_t^3 + \varepsilon_t \tag{7}$$

$$lnREWIND_t = lnGENWIND_t + lnGENWIND_t^2 + lnGENWIND_t^3 + \varepsilon_t \tag{8}$$

The nexus between solar electricity consumption vs. cumulative installed PV power and solar electricity generation can be expressed as:

$$lnRESOLAR_t = lnINSTALPV_t + lnINSTALPV_t^2 + lnINSTALPV_t^3 + \varepsilon_t \tag{9}$$

$$lnRESOLAR_t = lnGENSOLAR_t + lnGENSOLAR_t^2 + lnGENSOLAR_t^3 + \varepsilon_t \tag{10}$$

The polynomial presentation of the relationship between final electricity consumption vs. energy price index and air pollution is expressed as:

$$lnFC_t = lnENPRICE_t + lnENPRICE_t^2 + lnENPRICE_t^3 + \varepsilon_t \tag{11}$$

$$lnFC_t = lnPM2.5_t + lnPM2.5_t^2 + lnPM2.5_t^3 + \varepsilon_t \tag{12}$$

The bivariate model specification of the nexus between final electricity consumption vs. heating degree days and cooling degree days is expressed as:

$$lnFC_t = lnHDD_t + lnHDD_t^2 + lnHDD_t^3 + \varepsilon_t \tag{13}$$

$$lnFC_t = lnCDD_t + lnCDD_t^2 + lnCDD_t^3 + \varepsilon_t \tag{14}$$

The nexus between final electricity consumption vs. wind speed and relative humidity can be expressed as:

$$lnFC_t = lnWSPEED_t + lnWSPEED_t^2 + lnWSPEED_t^3 + \varepsilon_t \tag{15}$$

$$lnFC_t = lnRHUM_t + lnRHUM_t^2 + lnRHUM_t^3 + \varepsilon_t \tag{16}$$

The relationship between heating and cooling degree days and nexus between final electricity consumption and electricity generation can be presented as:

$$lnHDD_t = lnCDD_t + lnCDD_t^2 + lnCDD_t^3 + \varepsilon_t \tag{17}$$

$$lnFC_t = lnELEGEN_t + lnELEGEN_t^2 + lnELEGEN_t^3 + \varepsilon_t \tag{18}$$

Based on both conceptual framework (Scheme 1) and descriptive characteristics (Box 1) of the study, we adopt kernel-based regularized least squares (KRLS)––a machine learning algorithm with econometric attributes. Contrary to existing traditional econometric techniques, the KRLS technique develops pointwise derivatives and average marginal effects, hypothesis testing, and produces unbiased and consistent estimates (Ferwerda et al., 2017; Sarkodie and Owusu, 2020). Similarly, the KRLS algorithm outweighs existing machine learning techniques with challenges of misspecification bias over statistical inferences––thus, provides flexible and interpretable parameters amidst regression and classification conundrum with unspecified functional form. The KRLS estimator is useful for empirical analysis that involves learning of data creating procedure, model-driven causal interpretation, prediction, and missing data imputation (Hainmueller and Hazlett, 2014). For brevity, the generic specification of the conceptualized model can be expressed as:

$$\ln FC_t = \begin{array}{c} \partial \ \ln FC_{t-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \varepsilon_t \end{array} \tag{19}$$

$$lnRESOLAR_t = \begin{array}{c} \partial \ \ln RESOLAR_{t-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \beta_8 \ lnGENSOLAR_t + \\ \beta_9 \ TS_t + \beta_{10} \ lnINSTALPV_t + \varepsilon_t \end{array} \tag{20}$$

$$lnREWIND_t = \begin{array}{c} \partial \ \ln REWIND_{t-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \beta_8 \ \ln GENWIND_t + \\ \beta_9 \ TS_t + \beta_{10} \ \ln INSTALWIND_t + \beta_{11} \ DEW_t + \varepsilon_t \end{array} \tag{21}$$

$$lnFC_{HHt} = \begin{array}{c} \partial \ \ln FC_{HHt-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \beta_8 \ lnELEGEN_t + \\ \beta_9 \ TS_t + \beta_{10} \ lnPS_t + \beta_{11} \ DEW_t + \varepsilon_t \end{array} \tag{22}$$

$$lnFC_{INDt} = \begin{array}{c} \partial \ \ln FC_{INDt-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \\ \beta_8 \ TS_t + \beta_9 \ lnPS_t + \beta_{10} \ DEW_t + \varepsilon_t \end{array} \tag{23}$$

$$lnFC_{CPt} = \begin{array}{c} \partial \ \ln FC_{CPt-1} + \beta_1 \ \ln WSPEED_t + \beta_2 \ \ln CDD_t + \beta_3 \ \ln HDD_t + \beta_4 \ \ln PM2.5_t \\ +\beta_5 \ \ln PRECIP_t + \beta_6 \ \ln ENPRICE_t + \beta_7 \ \ln RHUM_t + \beta_8 \ lnELEGEN_t + \\ \beta_9 \ TS_t + \beta_{10} \ lnPS_t + \beta_{11} \ DEW_t + \varepsilon_t \end{array} \tag{24}$$

where $\partial, \beta_1, \ldots, \beta_k$ are average marginal effects to be estimated using the KRLS estimator, and ε_t denotes the error term. The expanded version of the KRLS algorithm is presented in Hainmueller and Hazlett (2014).

2.2. Model validation

The estimated models were validated using the post-estimation tests of the machine learning algorithm including pointwise marginal effects, lambda (i.e., to control the trade-off between fitness of the model and complexity selected through optimization), tolerance (i.e., to achieve convergence by controlling the sensitivity of lambda through optimization), goodness-of-fit (R-square) of the selected model, and looloss (sum of squared of leave-out-one error). Heterogeneous effects of the six estimated models were examined via the quantile function of the pointwise derivatives. Besides, the independence of the residuals was further examined using the CUSUM test––with results presented in Charts 2–3. We find that the residuals of all the time series are within the 95% confidence band––implying the estimated coefficients are constant over time. The CUSUM test further reveals no potential issues of residual structural breaks––hence, confirm the stability of the estimated parameters.

3. Results & discussion

The empirical estimation begins with a bivariate assessment of––wind electricity consumption vs. cumulative installed wind turbine capacity and wind electricity generation in Fig. 1, solar electricity consumption vs. cumulative installed PV power and solar electricity generation in Fig. 2, final electricity consumption vs. energy price index and air pollution in Fig. 3, final electricity consumption vs. heating degree days and cooling degree days in Fig. 4, and final electricity consumption vs. wind speed and relative humidity in Fig. 5. The relationship between heating degree days and cooling degree days, and nexus between final electricity consumption and electricity generation are depicted in Fig. 6. Using a polynomial estimation procedure, we find that installed wind turbine capacity predicts wind electricity consumption by 96% whereas wind electricity generation predicts wind electricity consumption by 100% (Fig. 1). Besides, a perfect positive monotonic relationship is observed––as both installed PV power and solar electricity generation predict solar electricity consumption by 100% (Fig. 2). In

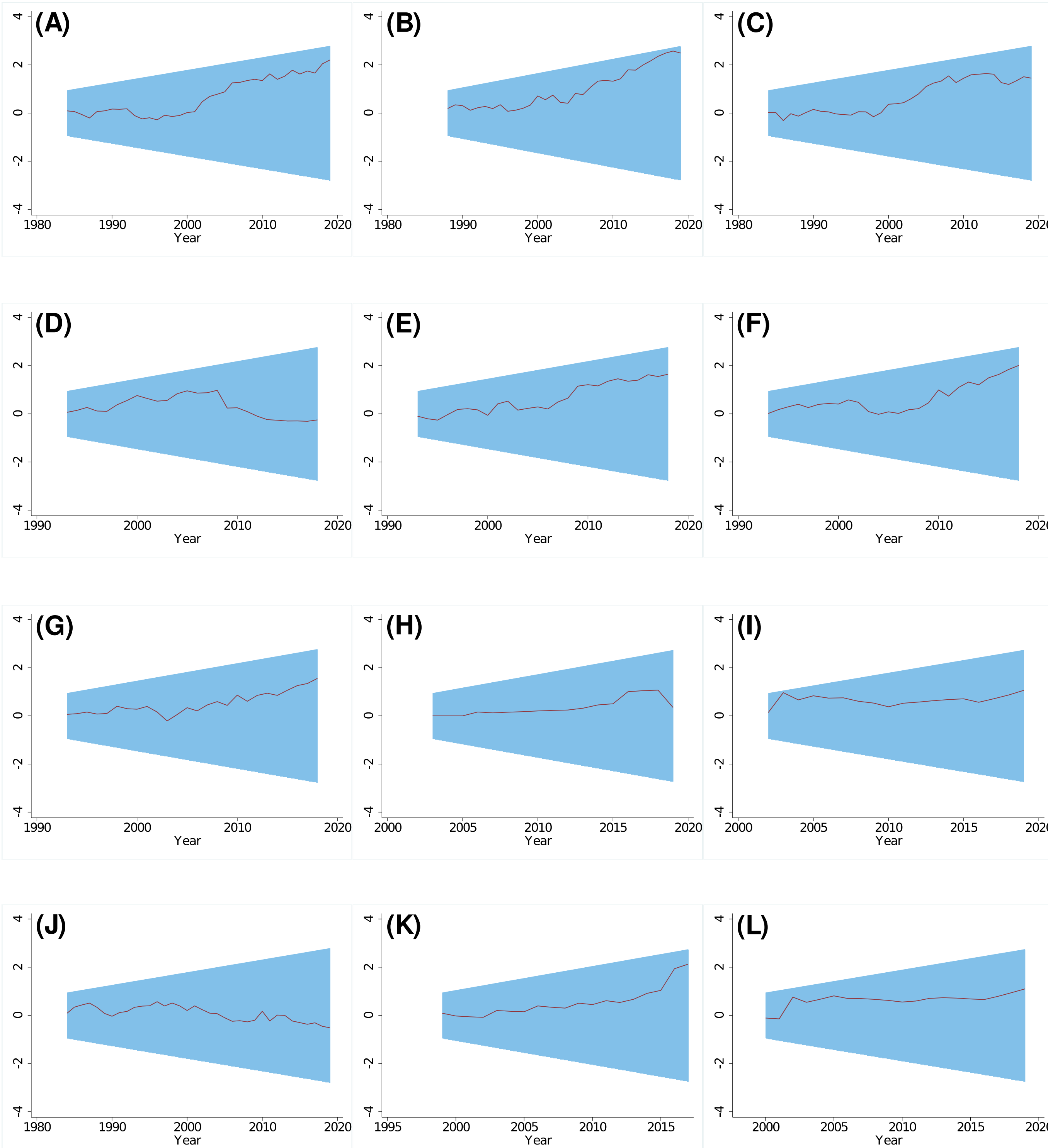


Chart 2. Parameter stability test (A) Cooling degree days (B) Electricity generation (C) Energy price (D) Industry sector energy use (E) Commercial and public services energy use (F) Households energy use (G) Final consumption (H) Solar generation (I) Wind generation (J) Heating degree days (K) Cumulative installed PV power (L) Cumulative installed wind turbine capacity.

both scenarios of solar and wind energy, the contribution of renewable energy technologies to the energy portfolio depends on installation technology and generation capacity. In contrast, an inverse-N structural relationship exists between final electricity consumption vs. energy price index and air pollution by a predictive power of 63% and 36%, respectively (Fig. 3). While low electricity consumption is linked to low energy price index, high energy price index explains high electricity consumed. Yet, increasing energy price index declines electricity consumption after a turning point in price index––thus, long-term energy price index has mitigation effect on electricity consumption. This decline might not be due to direct growth in energy prices but is indirectly linked to energy efficiency. In contrast, long-term intensity of ambient air pollution declines electricity consumption. In another scenario, N-structural relationship occurs between final electricity consumption vs. heating

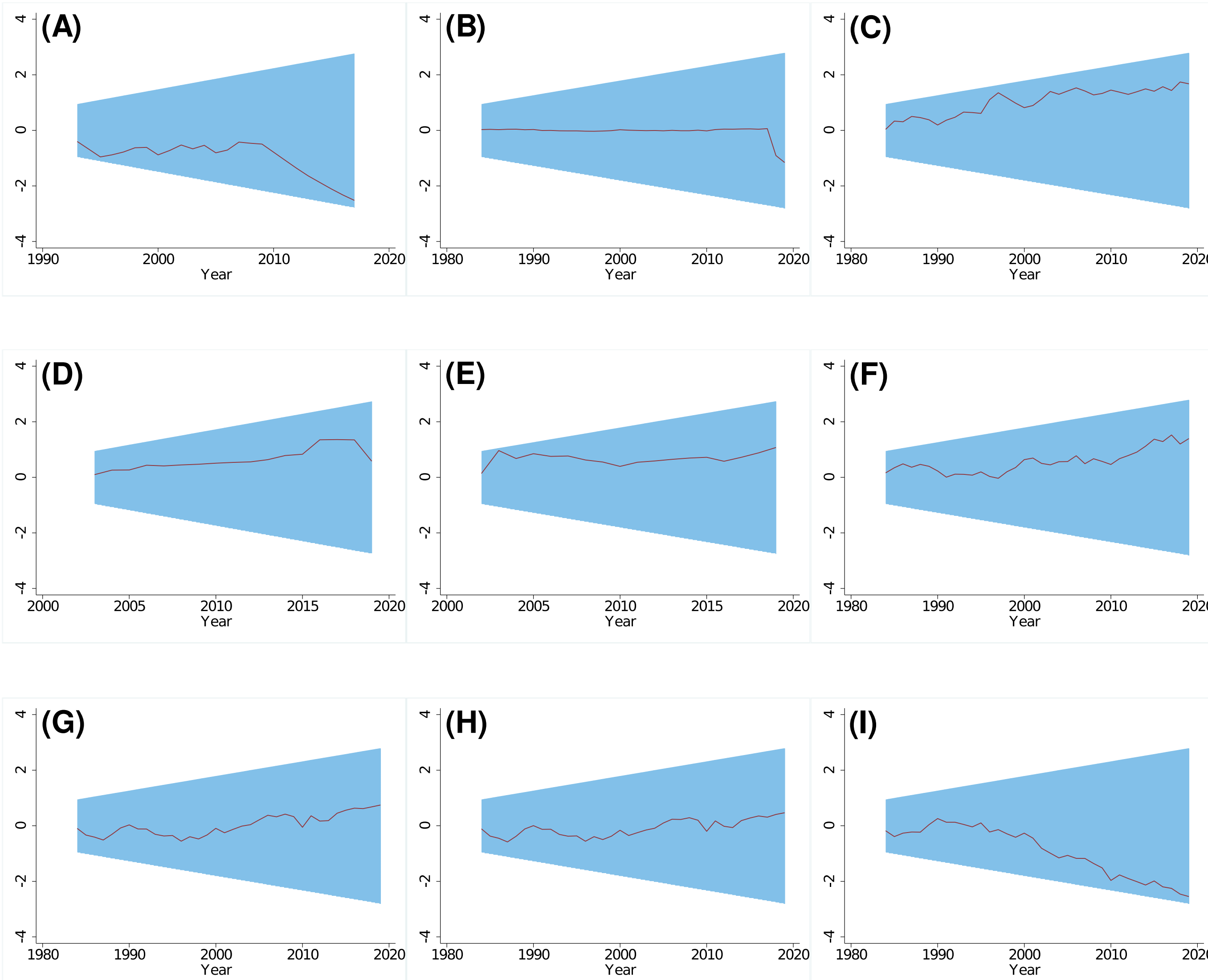


Chart 3. Parameter stability test (A) Air pollution (B) Precipitation (C) Surface pressure (D) Solar electricity consumption (E) Wind electricity consumption (F) Relative humidity (G) Dew/Frost point (H) Earth skin temperature (I) Wind speed.
Legend: Light blue color denotes 95% confidence band whereas the red line represents the estimated parameter.

degree days and cooling degree days by a predictive power of 18% and 11%, respectively (Fig. 4). Contrary, increasing wind speed is associated with a reduction in electricity consumption whereas high level of relative humidity has a positive monotonic relationship with electricity consumption at a predicted power of 25% and 18%, respectively (Fig. 5). Cooling degree days predict heating degree days by 41%––in a negative monotonic relationship [Fig. 6(A)]. This implies heating degree days decline with increasing cooling degree days––corresponding to the two prominent seasons namely summer and winter. Growth in electricity generation predicts long-term changes in final electricity consumption by 62%. The variations in the prediction presented in Fig. 6(B) reveal the possibility of unobserved factors not explained by electricity generation.

Next, we constructed six multivariate models that account for omitted-variable bias, and heterogeneous effects in electricity, solar, wind, household, industrial, and commercial consumption function. The resultant parameters of the effect of ambient air pollution and meteorological factors on electricity consumption are presented in Table 2. The error metric namely goodness-of-fit test shows R-square between 88 and 100% of electricity consumption (i.e., final electricity, solar electricity, wind electricity, household electricity, industrial electricity, and commercial electricity) explained by the regressors. The significant ($p < 0.01$) positive parameter of the lagged-final electricity ($Electricity_{t\text{-}1}$) in column 2, lagged-solar electricity ($Solar_{t\text{-}1}$) in column 3, lagged-wind electricity ($Wind_{t\text{-}1}$) in column 4, lagged-household electricity ($Household_{t\text{-}1}$) in column 5, lagged-industrial electricity ($Industry_{t\text{-}1}$) in column 6, and lagged-commercial electricity ($Commercial_{t\text{-}1}$) in column 7––reveal historical electricity consumption trends influence existing and future electricity consumption patterns by 23%, 19%, 11%, 32%, 22%, and 26%, respectively. Electricity generation has statistically strong positive relationship with households and commercial electricity consumption. This implies that increasing electricity generation increases electricity demand in households and commercial sector by 0.10%–0.17%.

3.1. Electricity consumption vs. wind speed

While a positive relationship is observed between wind speed and wind electricity consumption, a significant negative effect of wind speed on solar, household and commercial electricity consumption is evident. Wind speed distribution declines solar, households, and commercial electricity consumption by 0.06–0.56%. Variation in wind speed is directly linked to the height of wind turbines––implying the

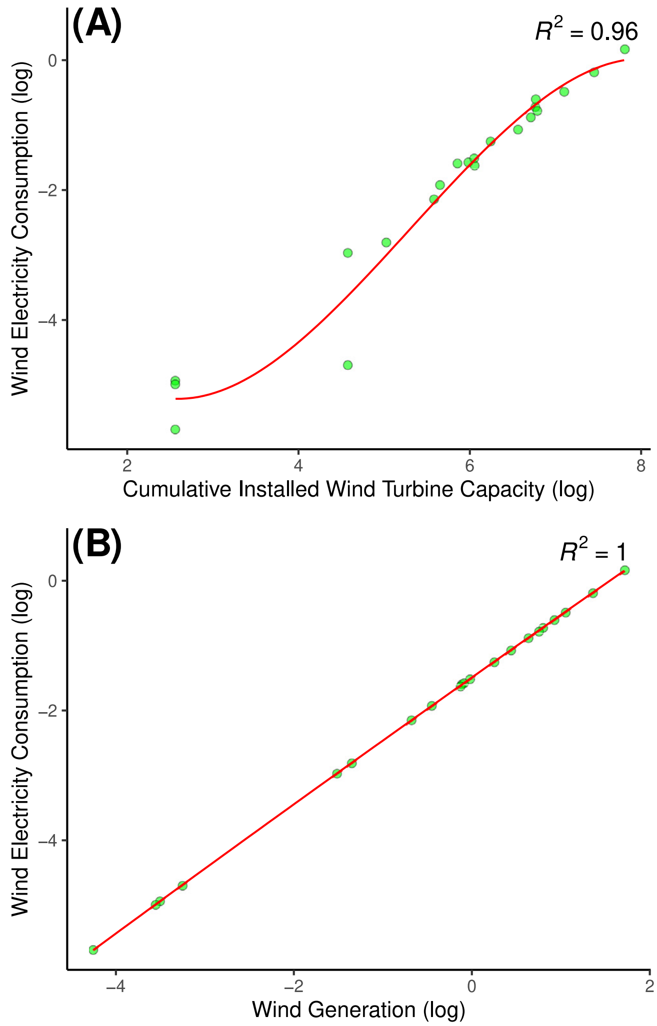


Fig. 1. Wind electricity consumption vs. (A) Cumulative installed wind turbine capacity (B) Wind electricity generation.

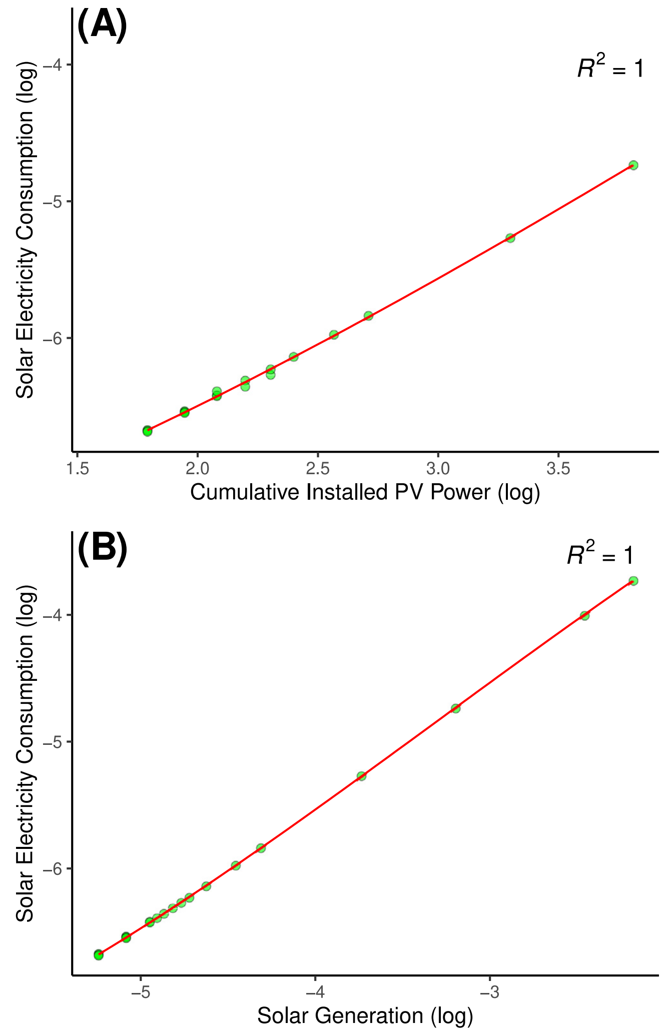


Fig. 2. Solar electricity consumption vs. (A) Cumulative installed PV power (B) Solar electricity generation.

generation capacity of wind turbines in relation to wind speed depends heavily on hub elevation (Tester et al., 2012). The negative effect of wind speed on electricity consumption can be linked to the importance of other energy sources in supplementing wind power variabilities and meeting electricity demand in households, industry, commercial and public sectors (Bell et al., 2015). Besides, wind speed distribution plays the natural ventilation role in buildings across households, industry, commercial and public sectors, hence, affecting indoor cooling and heating––which declines electricity consumption depending on building orientations and wind angles (Huifen et al., 2014).

3.2. Electricity consumption vs. cooling and heating degree days

Almost all the estimated parameters on CDD reveals a significant ($p < 0.01$) negative relationship with electricity consumption excluding commercial. This implies cooling degree days decline electricity consumption by 0.10–0.69%. In contrast, heating degree days increase final, households, and commercial electricity consumption by 0.09–0.22% whereas heating degree days decline solar, wind and industrial electricity consumption by 0.13–0.86%. Because heating degree days imply winter season, limited sunlight and high concentrations of dew/frost point and snow hamper solar and wind electricity generation, hence, affect electricity consumption from solar and wind sources. Thus, such long-term scenario may affect electricity consumption of industries that depend heavily on wind and solar resources––but may perhaps be complemented by hydro-power-induced electricity supply. In Norway, the heating degree days outweigh cooling degree days. Historical trends reveal average heating degree days of 6968.786 °C-d compared to 1224 °C-d cooling degree days. This implies that more electricity is required during winter to meet heating conditions compared to air conditioning requirements during summer––which is highly unlikely (except high heat gains) due to cool natural ventilation. Building orientations affect heat gains and heat losses through the solar radiation process and infiltration, hence, disrupts the heating and air conditioning dynamics in buildings––affecting electricity consumption during summer and winter seasons (Oropeza-Perez and Østergaard, 2014). Thus, while heat gains via solar radiation through wind speed and wind angles decline electricity consumption through cooling in summer, heat losses through cold wind spur heating conditions in winter.

3.3. Electricity consumption vs. ambient air pollution and energy prices

Climate change and its impact affect domestic weather patterns including causing dynamic changes in atmospheric concentrations of ambient air pollution. This form of weather-ambient air pollution interaction has long-term effect on electricity consumption. Here, Table 2 reveals that increasing levels of ambient air pollution decline final electricity consumption by 0.01%, solar electricity consumption by 0.03%, wind electricity consumption by 0.18%, and household electricity

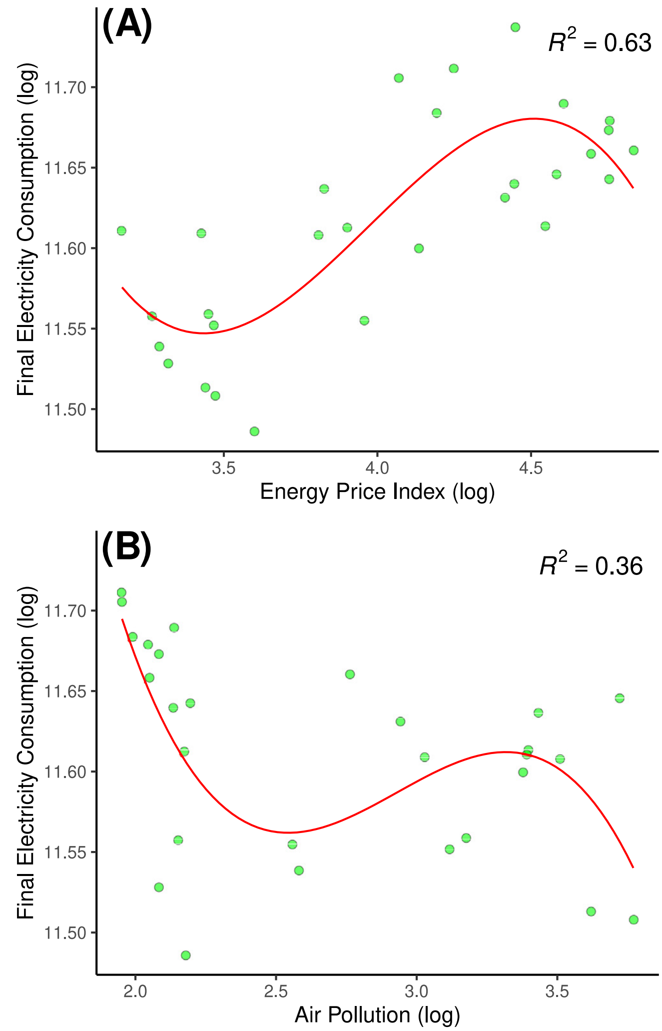


Fig. 3. Final electricity consumption vs. (A) Energy price index (B) Air pollution.

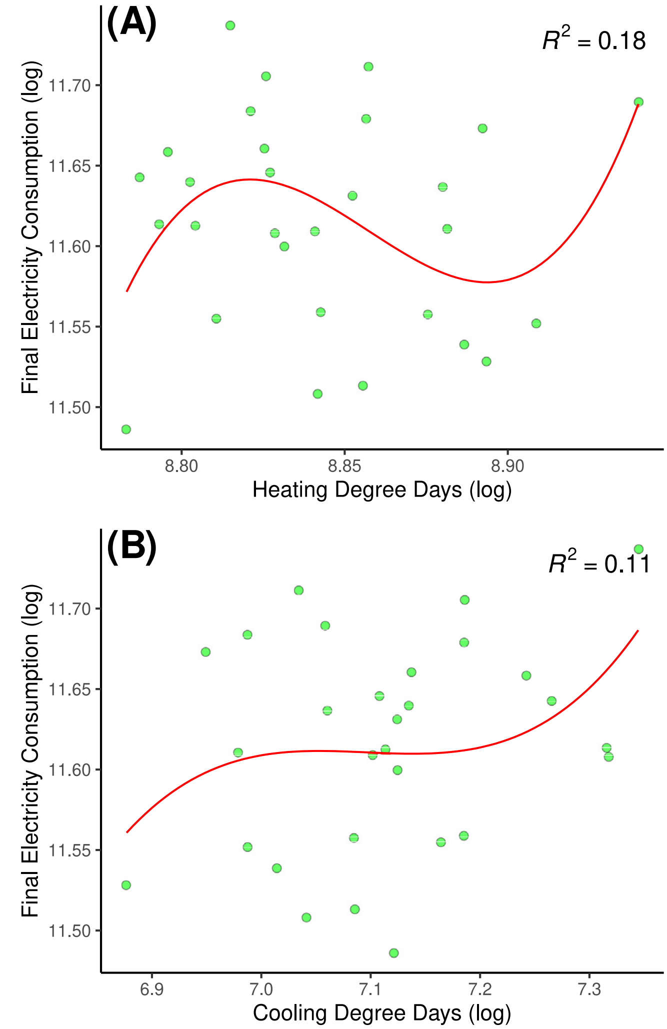


Fig. 4. Final electricity consumption vs. (A) Heating degree days (B) Cooling degree days.

consumption by 0.01%. Besides, a reduction in both solar and wind electricity consumption can be associated with the mitigation effect of wind and solar generation due to increasing levels of ambient air pollution (Son et al., 2020). The reduction effect of ambient air pollution on both wind and solar electricity consumption can be explained by its role in reducing downward thermal infrared (longwave) radiative flux and earth skin temperature––affecting solar and wind energy production (Bergin et al., 2017). Air pollution is reported to affect solar resources by reducing surfaces and tracking systems of solar PV, hence, affect direct solar radiation––leading to intermittent solar electricity generation (Li et al., 2017). The indirect radiative forcing effect of ambient air pollution includes alteration of the cloud cover affecting the insolation clearness index and air density––conditions crucial to solar and wind generation efficiency. In contrast to existing literature that found a positive relationship between residential electricity consumption and ambient air pollution (He et al., 2020), our study emphasizes that increasing levels of ambient air pollution spur both industry and commercial sector-based electricity consumption by 0.01%. The ambient air pollution-induced escalation effect of electricity consumption may be due to energy and carbon-intensive activities that usually occur in industrial and commercial sectors.

The affordability of energy plays an essential role in electricity access. We find that increasing energy price index improves electricity consumption including households and commercial sector, however, we observe a decline in solar, wind, and industrial sector-based electricity consumption. The reduction in wind and solar electricity consumption in relation to energy price index can be attributed to the low cost of hydropower aside from its reliability, however, solar systems appear attractive for commercial purposes due to their long-term profitability and cost-offset effect. Though renewable energy technologies are promising and environmentally friendly, however, the cost of the technology affects patronization due to market failures (Owusu and Asumadu, 2016).

3.4. Electricity consumption vs. meteorological conditions

Meteorological factors such as precipitation, earth skin temperature, surface pressure, humidity, and dew/frost point play important role in electricity generation, hence, affect electricity consumption. Positive changes in precipitation increase electricity consumption excluding industrial sector-based electricity by 0.03%–0.23%. Increasing precipitation drops atmospheric temperature, and reduces cloud cover accumulation of ambient air pollution due to its scavenging effects, hence, extends heating degree days by increasing heating requirements. The washout effect of precipitation intensity is reported to decline air pollutants, hence, improving the insolation clearness index (Yoo et al., 2014). Besides, the reduction effect of precipitation on ambient air pollution, ozone, and aerosols increases both wind and solar electricity consumption by improving longwave radiative flux and earth skin temperature––which underpin solar and wind energy production. Precipitation intensity improves solar resources by increasing surfaces of solar PV and tracking systems––due to accumulation of air pollutants

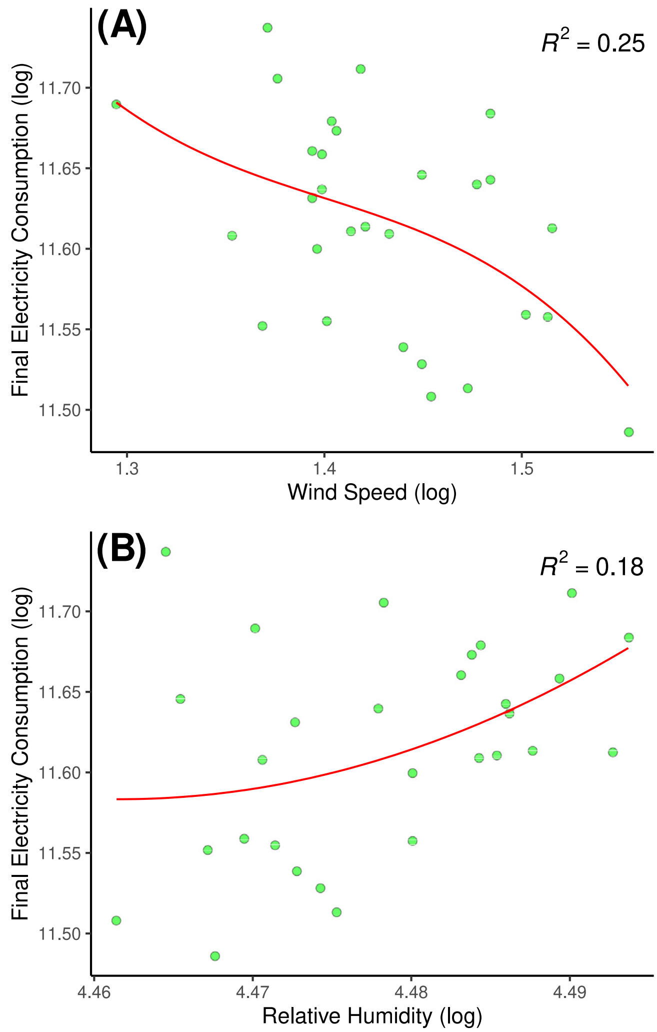


Fig. 5. Final electricity consumption vs. (A) Wind speed (B) Relative humidity.

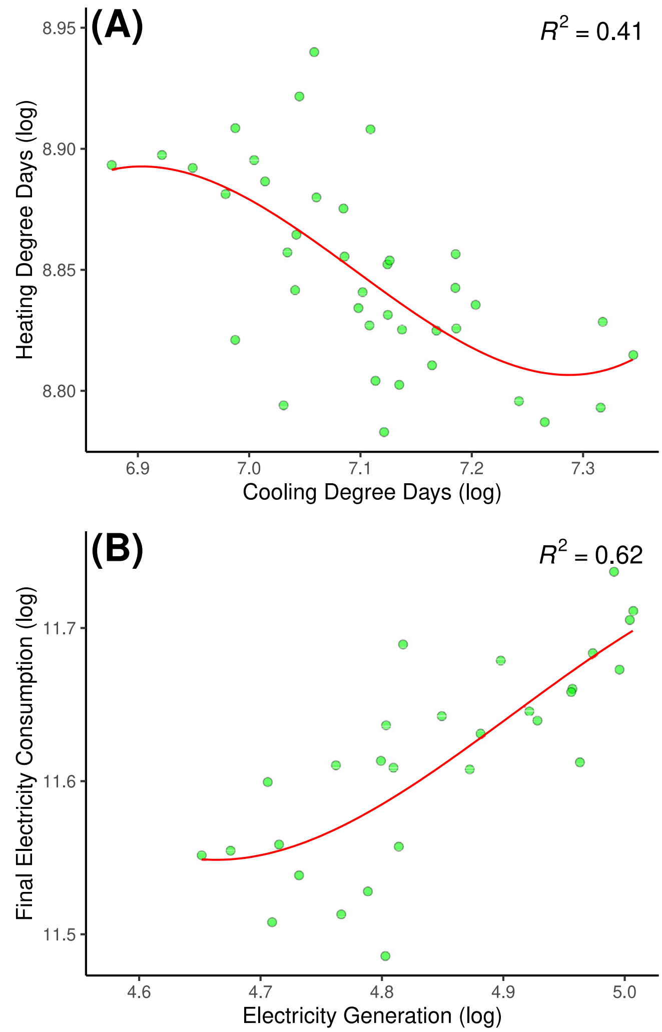


Fig. 6. Relationship between (A) Heating degree days vs. cooling degree days (B) Final electricity consumption vs. electricity generation.

that affect direct solar radiation––leading to sporadic solar electricity generation. The rising level of relative humidity is associated with increasing electricity consumption due to its role in rising earth skin temperature. We observe that an increase in relative humidity intensifies electricity consumption including solar, wind, households, and industry by 0.23%–1.30%. Similarly, increasing earth skin temperature escalates electricity consumption by 0.80%–1.30% whereas industrial and commercial sector electricity consumption depreciates by 0.90%–1.10%. Humidity and rising temperature are critical to wind and solar energy generation––and consequently, electricity consumption in cold climate regimes like Norway. The balancing point between earth skin temperature and humidity determines human comfort is the dew/frost point (Maia-Silva et al., 2020). Increasing levels of dew/frost point in typical summer seasons drop high temperatures and improve household and commercial cooling demands, hence, decline electricity consumption by 0.80%–1%. In contrast, rising levels of dew/frost point in winter seasons induce cold temperatures, hence, increases heating degree days due to increased heating requirements, thus, increasing electricity consumption by 0.90%–2.40%.

3.5. Solar electricity consumption vs. installed PV power and solar energy generation

In Fig. 2, the estimated results confirm a strong positive impact of both installed PV power and solar energy generation on solar electricity consumption by 0.14%. Several factors aside meteorological conditions affect the PV power conversion efficiency including power system specifications (i.e., power capacity, PV module, rated voltage and current), energy loss above and below the band-gap, PV collector-induced reflective losses, and limited photon-electron interaction (Asumadu and Owusu, 2016; Tester et al., 2012). This implies the effect of solar electricity generation on solar electricity consumption is determined by installed PV power and climatic factors.

3.6. Wind electricity consumption vs. installed wind turbine and wind energy generation

Our empirical analysis concurs the positive relationship between wind electricity and installed wind turbine, and wind energy generation in electricity consumption function evidenced in Fig. 1. We find that increasing scenarios of installed wind turbine capacity increases wind electricity consumption by 0.15% whereas wind electricity generation increases electricity consumption by 0.17%. The composition of wind turbines such as hub height, rotor blade (rotor diameter––swept area), nacelle (generator), and power-specifications––affects the efficiency and generational capacity while accounting for wind speed and air density (Hirth and Müller, 2016; Sarkodie and Owusu, 2016). Thus, the direct effect of wind electricity generation on wind electricity consumption depends heavily on the dynamics of installed wind turbine capacity and meteorological factors.

Table 2
Effect of ambient air pollution, and meteorological factors on electricity consumption.

Parameter	Electricity	Solar	Wind	Household	Industry	Commercial
$Electricity_{t-1}$	0.232*** [0.029]	---	---	---	---	---
$Solar_{t-1}$	---	0.196*** [0.001]	---	---	---	---
$Wind_{t-1}$	---	---	0.113*** [0.001]	---	---	---
$Household_{t-1}$	---	---	---	0.320*** [0.004]	---	---
$Industry_{t-1}$	---	---	---	---	0.223*** [0.038]	---
$Commercial_{t-1}$	---	---	---	---	---	0.261*** [0.012]
Wind Speed	−0.055 [0.035]	−0.561*** [0.007]	0.144 [0.092]	−0.023*** [0.006]	0.033 [0.046]	−0.206** [0.026]
CDD	−0.018 [0.016]	−0.167*** [0.003]	−0.692*** [0.048]	−0.005* [0.003]	−0.010*** [0.021]	0.044** [0.012]
HDD	0.087* [0.048]	−0.190*** [0.005]	−0.863*** [0.047]	0.183*** [0.004]	−0.139*** [0.031]	0.229** [0.015]
$PM_{2.5}$	−0.007** [0.003]	−0.031*** [0.000]	−0.176*** [0.006]	−0.008*** [0.000]	0.008** [0.004]	0.009** [0.002]
Precipitation	0.017 [0.018]	0.226*** [0.003]	0.181*** [0.043]	0.032*** [0.003]	−0.115*** [0.022]	0.132*** [0.013]
Energy price	0.014*** [0.003]	−0.014*** [0.000]	−0.019 [0.014]	0.003*** [0.001]	−0.010** [0.004]	0.018*** [0.002]
Humidity	0.969*** [0.215]	0.913** [0.044]	1.275* [0.557]	0.231*** [0.039]	1.247*** [0.258]	−0.074 [0.164]
Earth Temperature	---	1.200*** [0.000]	1.300*** [0.003]	−0.900*** [0.000]	0.800*** [0.002]	−1.100*** [0.001]
Installed PV	---	0.139*** [0.000]	---	---	---	---
Solar generation	---	0.136*** [0.000]	---	---	---	---
Installed wind turbine	---	---	0.145*** [0.001]	---	---	---
Wind generation	---	---	0.171*** [0.002]	---	---	---
Dew/frost point	---	---	2.400*** [0.003]	−0.800*** [0.000]	0.900*** [0.001]	−1.000*** [0.001]
Surface pressure	---	---	---	−0.255 [0.216]	−6.081*** [1.543]	7.349*** [0.936]
Electricity generation	---	---	---	0.102*** [0.003]	---	0.169*** [0.013]
Lambda	0.44	0.00	0.02	0.03	0.32	0.07
Tolerance	0.03	0.02	0.02	0.03	0.03	0.03
Sigma	8.00	11.00	12.00	12.00	11.00	12.00
Eff. df	14.68	16.86	17.31	25.36	16.77	23.14
R^2	0.92	1.00	1.00	1.00	0.88	0.99
Looloss	0.59	3.34	11.39	0.55	1.29	1.26

Follow-ups: *,**,*** represent the statistical significance of the estimated parameters at *p-value* < 0.10, *p-value* < 0.05, & *p-value* < 0.01.

4. Conclusion

This study examined the impact of climate change variabilities on electricity consumption. Using Norway as a case study, we adopted the kernel-based regularized least squares (KRLS) algorithm to estimate the average marginal effect of parameters from 1981 to 2019. Contrary to previous studies that are limited to humidity and temperature effects on energy, we employed numerous variables to capture pollutants and meteorological dynamics of climate change heterogeneity, and historical effects to produce robust and consistent estimates. We found that historical and behavioral patterns affect electricity consumption from solar, wind, and across households, industrial sector, and commercial sector electricity consumption. This implies the marginal propensity of electricity consumption is determined by historical tendencies. Thus, efforts to improve efficiency in the electricity sector would require awareness and willingness to adapt via changes in consumption patterns. Our study demonstrated that energy price index is critical to the adoption of solar and wind energy technologies.

The empirical assessment revealed the effect of earth skin temperature and humidity increases electricity consumption whereas radiative forcing effect of ambient air pollution decreases electricity consumption. Contrary, scavenging and washout effects of rainfall intensity on ambient air pollution improve both wind and solar electricity consumption. Rising levels of earth skin temperature, and humidity increases solar and wind electricity consumption whereas dew-frost point drops temperature, and humidity to improve human comfort. The distributional effect of wind speed declines solar, households, and commercial electricity consumption. Wind speed plays the natural ventilation role in buildings across households, industry, commercial and public sectors, hence, affect indoor cooling and heating circulation––which declines electricity consumption based on building orientations and wind angles. In a power generation scenario, the height of wind turbines underpins variations in wind speed––hence, affects wind energy generation. The reduction effect of wind speed on electricity consumption is directly linked to air circulation during summer seasons, hence, reduces energy requirement in households, industrial, commercial and public sectors.

The effect of technological advancement in electricity consumption was evident in the role of both cumulative installed photovoltaic power and installed wind turbine capacity in promoting electricity consumption. While the variability of weather patterns affects electricity generation, the efficiency and generation capacity of solar and wind depend on the specification of PV modules and wind turbines. In this regard, technological innovation is a requirement to reduce energy loss due to band-gap dynamics of PV material and collector, and improve photon and wind harvesting. While our study failed to empirically account for module specifications of solar PV and wind turbines in the effect of air pollution and meteorological factors on electricity consumption, future research in this scope will be worthwhile.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Formal analysis, Funding acquisition, Methodology, Software, Validation, Visualization, Writing – review & editing. **Maruf Yakubu Ahmed:** Writing – original draft. **Phebe Asantewaa Owusu:** Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Asumadu, S.S., Owusu, P.A., 2016. The potential and economic viability of solar photovoltaic power in Ghana. Energy Sources A-Recover. Utilization Environ. Eff. 38 (5), 709–716. https://doi.org/10.1080/15567036.2015.1122682.

Bell, W.P., Wild, P., Foster, J., Hewson, M., 2015. Wind speed and electricity demand correlation analysis in the Australian National Electricity Market: determining wind turbine generators' ability to meet electricity demand without energy storage. Econ. Anal. Policy 48, 182–191. https://doi.org/10.1016/j.eap.2015.11.009.

Bergin, M.H., Ghoroi, C., Dixit, D., Schauer, J.J., Shindell, D.T., 2017. Large reductions in solar energy production due to dust and particulate air pollution. Environ. Sci. Technol. Lett. 4 (8), 339–344. https://doi.org/10.1021/acs.estlett.7b00197.

Beyene, T., Lettenmaier, D. P., & Kabat, P. J. C. c. (2010). Hydrologic impacts of climate change on the Nile River basin: implications of the 2007 IPCC scenarios. 100(3–4), 433–461.

Blanco, A.S., Gerlagh, R., Suh, S., Barrett, J.A., de Coninck, H., Diaz Morejon, C.F., ... Zhou, 2014. *Drivers, Trends and Mitigation*. United States. O Edenhofer, et al; Cambridge University Press, Cambridge, United Kingdom.

Blendon, R. J., Koonin, L. M., Benson, J. M., Cetron, M. S., Pollard, W. E., Mitchell, E. W., … Herrmann, M. J. J. E. i. d. (2008). Public response to community mitigation measures for pandemic influenza. 14(5), 778.

British Petroleum, 2018. BP statistical review of world energy. Retrieved from. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/downloads.html.

Ebinger, J., Vergara, W., 2011. Climate Impacts on Energy Systems: Key Issues for Energy Sector Adaptation. The World Bank.

EU, 2009. Directive 2009/28/EC of the European Parliament and of the council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing directives 2001/77/EC and 2003/30/EC. Off. J. Eur. Union 5, 2009 Retrieved from. https://buff.ly/3xxi4FI.

Ferwerda, J., Hainmueller, J., & Hazlett, C. J. (2017). Kernel-based regularized least squares in R (KRLS) and Stata (krls). J. Stat. Softw., 79(3), 1–26.

Godzimirski, J.M., 2014. The Norwegian energy security debate: Domestic and international dimensions. The Political Economy of Renewable Energy and Energy Security. Springer, pp. 116–136.

Hainmueller, J., Hazlett, C., 2014. Kernel regularized least squares: reducing misspecification bias with a flexible and interpretable machine learning approach. Polit. Anal. 22 (2), 143–168.

He, P., Liang, J., Qiu, Y.L., Li, Q., Xing, B., 2020. Increase in domestic electricity consumption from particulate air pollution. Nat. Energy 5 (12), 985–995.

Hirth, L., Müller, S., 2016. System-friendly wind power: how advanced wind turbine design can increase the economic value of electricity generated through wind power. Energy Econ. 56, 51–63. https://doi.org/10.1016/j.eneco.2016.02.016.

Houghton, J., 2001. 2001. Climate Change, The Scientific Basis.

Huifen, Z., Fuhua, Y., Qian, Z., 2014. Research on the impact of wind angles on the residential building energy consumption. Math. Probl. Eng. 2014, 794650. https://doi.org/10.1155/2014/794650.

IRENA. (2018). Global energy transformation — a roadmap to 2050. Retrieved from https://buff.ly/2Os1LYT.

Li, X., Wagner, F., Peng, W., Yang, J., Mauzerall, D.L., 2017. Reduction of solar photovoltaic resources due to air pollution in China. Proc. Natl. Acad. Sci. 114 (45), 11867. https://doi.org/10.1073/pnas.1711462114.

Magazzino, C., Mutascu, M., Sarkodie, S.A., Adedoyin, F.F., Owusu, P.A., 2021. Heterogeneous effects of temperature and emissions on economic productivity across climate regimes. Sci. Total Environ. 775, 145893. https://doi.org/10.1016/j.scitotenv.2021.145893.

Maia-Silva, D., Kumar, R., & Nateghi, R. (2020). The critical role of humidity in modeling summer electricity demand across the United States. Nat. Commun., 11(1), 1–8.

MOPE. (2021). Energy. Retrieved from https://www.regjeringen.no/en/topics/energy/id212/.

NASA, 2020. meteorological data sets. Retrieved from. https://nasa.gov.

OECD. (2018). Environmental risks and health. Retrieved from https://stats.oecd.org/.

Oropeza-Perez, I., Østergaard, P.A., 2014. Energy saving potential of utilizing natural ventilation under warm conditions – a case study of Mexico. Appl. Energy 130, 20–32. https://doi.org/10.1016/j.apenergy.2014.05.035.

Owusu, P., Asumadu, S.S., 2016. A review of renewable energy sources, sustainability issues and climate change mitigation. Cogent Eng. 3 (1), 1167990. https://doi.org/10.1080/23311916.2016.1167990.

Rogelj, J., Huppmann, D., Krey, V., Riahi, K., Clarke, L., Gidden, M., … Meinshausen, M. (2019). A new scenario logic for the Paris agreement long-term temperature goal. Nature, 573(7774), 357–363.

Rosenberg, E., Espegren, K.A., 2009. Energy Scenario Analysis Enova-IFE; Energiscenarioanalyser Enova-IFE.

Sarkodie, S.A., Owusu, P.A., 2016. The potential and economic viability of wind farms in Ghana. Energy Sources A: Recover. Utilization Environ. Eff. 38 (05), 695–701. https://doi.org/10.1080/15567036.2015.1122680.

Sarkodie, S.A., Owusu, P.A., 2020. How to apply the novel dynamic ARDL simulations (dynardl) and kernel-based regularized least squares (krls). MethodsX, 101160 https://doi.org/10.1016/j.mex.2020.101160.

Seljom, P., Rosenberg, E., Fidje, A., Haugen, J. E., Meir, M., Rekstad, J., & Jarlset, T. J. E. p. (2011). Modelling the Effects of Climate Change on the Energy System—A Case Study of Norway. *vol. 39(11)*, 7310–7321.

Son, J., Jeong, S., Park, H., Park, C.-E., 2020. The effect of particulate matter on solar photovoltaic power generation over the Republic of Korea. Environ. Res. Lett. 15 (8), 084004.

Sweerts, B., Pfenninger, S., Yang, S., Folini, D., Van der Zwaan, B., & Wild, M. J. N. E. (2019). Estimation of Losses in Solar Energy Production from Air Pollution in China since 1960 Using Surface Radiation Data. *vol. 4(8)*, 657–663.

Tester, J.W., Drake, E.M., Driscoll, M.J., Golay, M.W., Peters, W.A., 2012. Sustainable Energy: Choosing among Options. MIT press.

Vellinga, M., & Wood, R. A. J. C. c. (2002). Global climatic impacts of a collapse of the Atlantic thermohaline circulation. 54(3), 251–267.

Wilbanks, T., Bhatt, V., Bilello, D., Bull, S., Ekmann, J., Horak, W., … Schmalzer, D. J. U. D. o. E. P. (2008). Effects of Climate Change on Energy Production and Use in the United States. 12.

World Bank. (2020). World development indicators. Retrieved from http://data.worldbank.org/country.

Yalew, S. G., van Vliet, M. T., Gernaat, D. E., Ludwig, F., Miara, A., Park, C., … Iyer, G. J. N. E. (2020). Impacts of climate change on energy systems in global and regional scenarios. 5(10), 794–802.

Yoo, J.-M., Lee, Y.-R., Kim, D., Jeong, M.-J., Stockwell, W. R., Kundu, P. K., … Lee, S.-J. (2014). New indices for wet scavenging of air pollutants (O3, CO, NO2, SO2, and PM10) by summertime rain. Atmos. Environ., 82, 226–237. doi:https://doi.org/10.1016/j.atmosenv.2013.10.022.