# Regime switching effect of COVID-19 pandemic on renewable electricity generation in Denmark


## Abstract

Denmark has achieved remarkable success in renewable energy generation over the last several decades. However, the country's goals of meeting its 50% energy demand from renewable by 2030 and becoming independent of fossil fuel by 2050 are currently in jeopardy due to the COVID-19 pandemic, which emerged at the end of December 2019 in the Chinese city of Wuhan. This study, therefore, tries to see how COVID-19 affects renewable electricity generation in Denmark using the econometric framework. Several nonlinear estimation techniques such as Fourier ADL cointegration analysis and Markov Switching regression are used to estimate the relationship between the three channels of COVID-19 and renewable electricity generation. The result from the Markov Switching regression reveals that renewable electricity production in Denmark is adversely affected by the enforced lockdown as captured via the stringency index, economic support provided to tackle the pandemic, and daily confirmed deaths of COVID-19. Moreover, the causality test shows that the stringency index and daily confirmed deaths of COVID-19 are important predictors of renewable electricity, but the economic support index has weak causality with renewable electricity. The study finally presents some crucial policy suggestions for Denmark which can help the country achieve its renewable production goals.



**Keywords:** Denmark; Renewable electricity; COVID; lockdown; economic support; Nonlinearity

## 1.0 Introduction

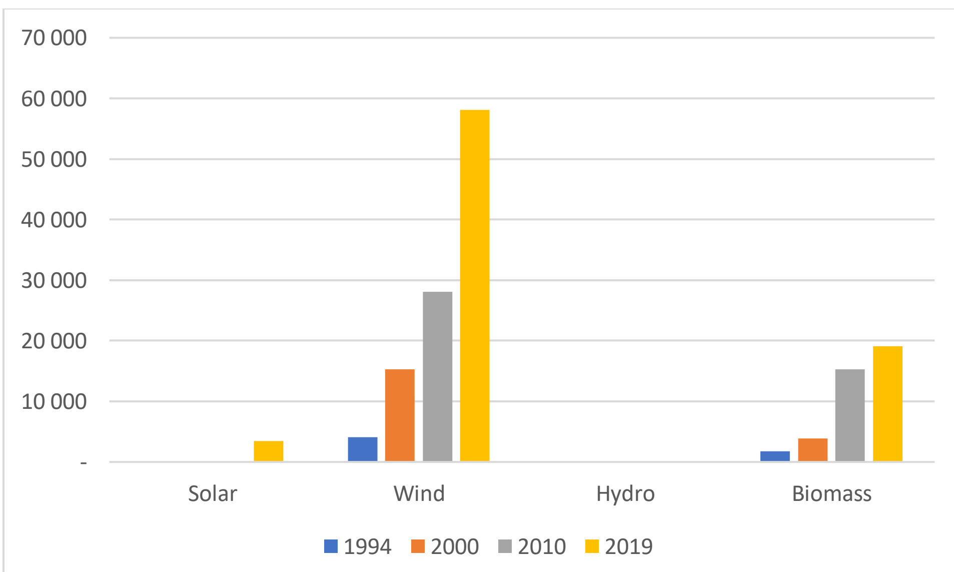
With over 87 million confirmed cases of infection and almost 2 million deaths in about 222 countries across the globe, as of January 9th, 2021 [1], the COVID-19 pandemic has secured significant attention globally. It has affected almost every section of life. It has also prompted varieties of actions and reactions from governments across levels and their citizens. Policies, rules, and regulations are being administered to curb its spread and withdrawn or softened times to permit the execution of human and economic activities. With all these measures in place, the Organization for Economic Co-operation and Development (OECD) predicts that global Gross Domestic Product (GDP) is going to be reduced by 7.6 per cent in 2020 if there is a second wave of the pandemic, but 6 per cent drop if the second wave is avoided. They further mentioned that this drop might extend beyond the year 2020 if there is another outbreak towards the end of the year. And, if this happens, the growth accrued over the last five years could be lost by the end of the year 2021 [2].

Although the pandemic is undoubtedly a threat to the economy, the same cannot be said for the renewable sector. On the one hand, this pandemic can act as a catalyst to reduce emissions, increase employment and economic growth and, therefore, can be creative destruction by replacing the old fossil fuel [3, 4]. But on the other hand, renewable energy development has encountered a challenge because of the pandemic, as COVID-19 has affected the supply chain as well as the manufacturing process of renewables. This disruption in the supply chain is again causing trouble in manufacturing, leading to a contraction in the renewable energy sector [5]. Also, the import and export of solar panel shipment experienced turbulence all around the world because of the global shutdown [6]. Specifically, wind energy stands to encounter significant risk due to the pandemic. Hence, Denmark, a country that experiences strong winds from the North Sea and the Baltic Sea and currently the global leader in wind energy development, also faces uncertainty in its renewable industry [7]. The country's over-reliance on wind energy makes it vulnerable to crisis events like COVID-19.

According to the Environmental performance index of 2020, Denmark is the greenest country in the world, excelling in air quality, sanitation, safe drinking water, waste management, and leading the world in tackling climate change with a target to cut GHG emissions by 70% by 2030 [8]. Over the last several decades, this country has achieved remarkable success in renewable energy development. The policies introduced in developing renewable energy to stabilize the climate are lessons for other countries. This proves that with appropriate policies, the government can mitigate the gap between the primary cost of investment payment and getting the benefits out of the renewable industry [9].

The electricity generation in Denmark mostly depends on wind energy, as has been indicated in Figure 1. Before the 1970s, this country depended primarily on imported oil. But the country's quest for energy independence began after the oil crisis of 1973-74. Since then, Denmark has chosen and invested a huge amount in renewables, especially in wind energy generation. As a result, renewable production amounted to 47% of its total energy generation in 2019 [10]. While the global target is set at making renewables generate 50% of the global energy supply by 2050, 'Denmark's targets are to make renewables supply more than half of her energy demands by 2030 and to have done away with fossil fuels for energy generation by 2050 [11, 12].

**Figure 1: Gross electricity production from renewable (TJ) in Denmark**

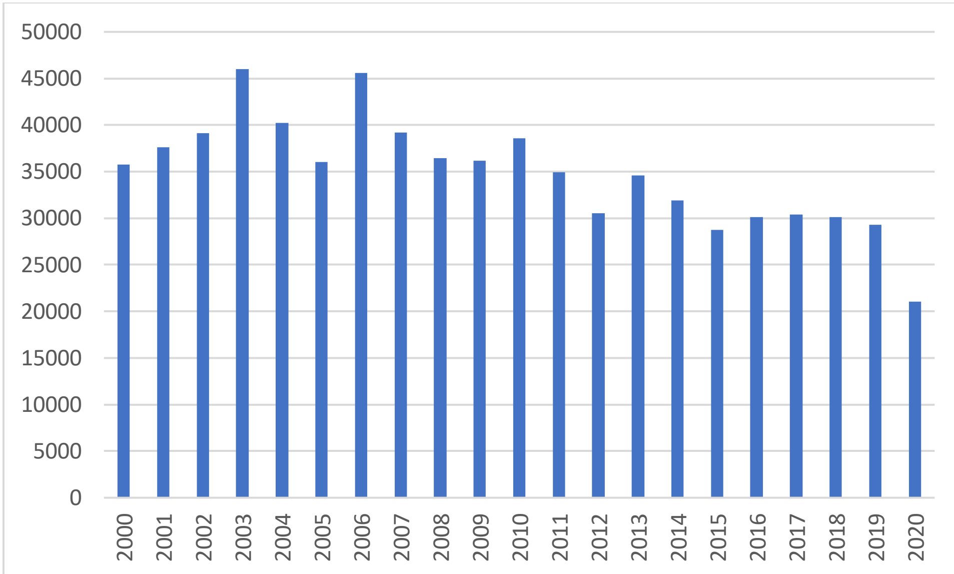



Source: Danish Energy Agency (2020)

Denmark is a leading player in Variable Renewable Energy (VRE) system integration and energy-saving technologies that maximize energy and minimizes heat, such as the combined heat and power (CHP) [13]. The country is therefore rightfully nick-named the laboratory of green solutions. The Energy Trilemma Index of the World Energy Council [14] ranks Denmark as one of the top three countries with a score of 84 out of 100. However, the country ranks poorly in terms of energy security and energy equity compared to other neighbouring economies. The countries with a diversified energy system and a higher level of hydrocarbon power sources are ranked highly in terms of energy security. Nevertheless Denmark's energy production from hydro is almost zero, and the country relies heavily on wind power. The countries ranked highly in this category can also counteract and properly respond to any system shocks with minimal disturbance like COVID-19. Therefore, Denmark seems to be suffering from a lack of system resilience. In terms of energy equity, Denmark is not even in the top ten countries. Energy equity refers to countries with low energy costs, but consumers in Denmark have to pay high rates for electricity compared to other European countries, and taxes of energy are three times greater than that of the average in Europe [15, 16]. Therefore, Denmark has to take account of these issues while making its transition towards clean energy.

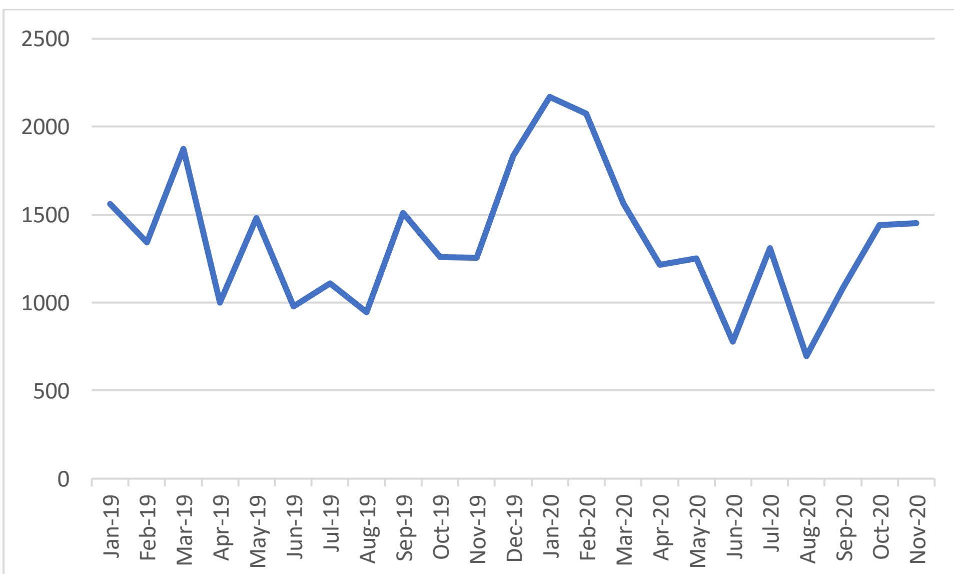
The COVID-19 pandemic has hit the entire supply chain of Denmark's energy sector, starting from commodities to components. This is evident from figure 2 where the gross electricity generation in Denmark declined substantially for the first time since 2000. Furthermore, figure 3 shows that the decline in gross electricity generation can be attributed to the decline in net electricity production from wind turbines. This again is the reflection of the argument made by Bloomberg New Energy Finance which said that over-reliance on one particular source of renewable energy can be a damaging factor during crisis events [7]

**Figure 2: Gross electricity production (GWh.) in Denmark**




Source: Danish Energy Agency

**Figure 3: Net Electricity Production (GWh.) from wind turbines in Denmark**

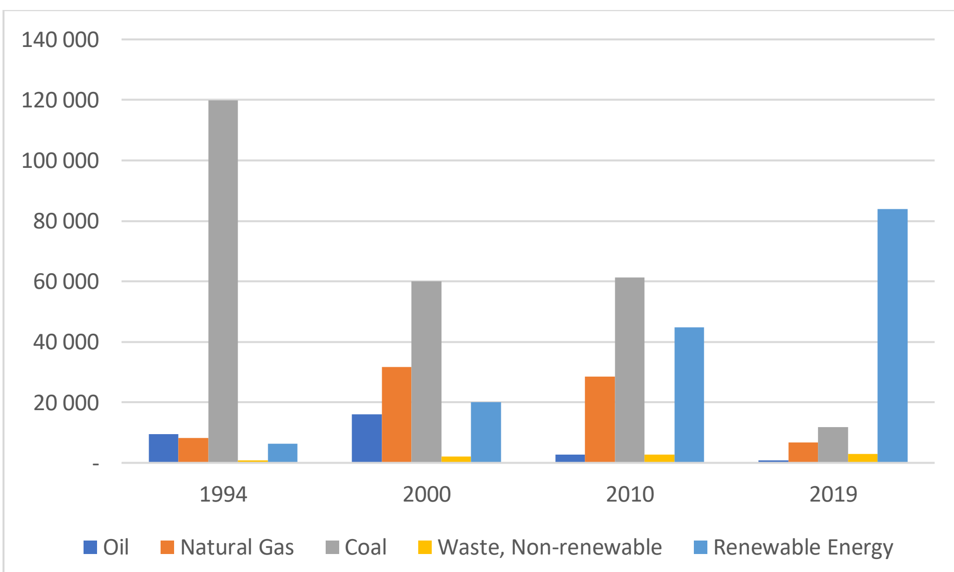



Source: Danish Energy Agency

Owing to the above discussion, our study contributes to the empirical literature in several ways. First, the effects of the COVID-19 pandemic may not be uniform globally, because of the differences in containment measures and levels of their deployment across regions, countries, and geographies. Therefore, economic, geographical, political, and other peculiarities, including strictness of containment measures, relief, or palliative support measures, will provide quality information on the effect of the pandemic [17]. Denmark was recorded to have relatively fewer infections when compared to other European countries during the early period of the pandemic, due to prompt government interventions such as the introduction of strict lockdown, social distancing, and government support [18]. These measures, without a doubt, will have their short- and long-term implications on the state of the country.

We are specifically interested in the renewable generation of Denmark because its doggedness on sustainable energy development, triggered by the 1970s oil crisis, has placed them on a high pedestal in renewable energy solutions. This journey is in line with the global goal to generate all her energy independent of the environmental-damaging, carbon dioxide-emitting fossil fuels. The electricity generation trend of renewable over the last several decades as shown in figure 4, indicates a very rapid increase and a high potential. Furthermore, since renewable energy sources have notable effects on economic growth, understanding its generation may indicate a path toward economic recovery during and after the pandemic.

**Figure 4: Gross Electricity production by fuels (TJ) in Denmark**




Source: Danish Energy Agency

Second, our study highlights three channels by which this pandemic can exert its influence on renewable electricity generation in Denmark. First Channel is the stringency of the restriction and lockdown policies which make investments in the renewable industry uncertain. These lockdown policies also put construction as well as the operation of renewable plants in jeopardy. The second channel is via the economic stimulus that the government has implemented. The Danish government will have to sacrifice a significant amount of its GDP to attain the objective of being carbon neutral within 2050. But the government has already spent approximately 26% of its GDP to tackle the COVID-19 pandemic within its boundary [19]. Therefore as more and more money is needed to tackle the virus, more financial resources will be diverted away from meeting the goals of climate mitigation. The third channel is via the COVID-19 pandemic itself. We hypothesize that the COVID-19 pandemic will have a multiplier effect on renewable energy generation because it captures lockdown policies, health containment policies, economic stimulus as well as the dread of the pandemic itself.

Third, only a few studies have empirically examined the effect of COVID-19 on the electricity sector using the econometric framework. For example, Carvalho et al. [20] used Joinpoint regression and showed that COVID-19 affected electricity consumption significantly, although the reductions were different across geographic regions. Norouzi et al. [21] on the other hand, explored the impact of COVID-19 on Spain's electricity market and they found that observations of deaths and cases due to COVID-19 were negatively associated with energy prices. In other studies, Alkhraijah et al.[22], Geraldi et al. [23], Bielecki et al. [24], Iqbal et al. [25], and Aruga et al. [26] also examined the association between energy consumption and COVID but only some of these studies utilized the econometric methods. This study is more similar to that of Alhajeri et al. [27] who provided evidence of COVID-19 preventing actions leading to a reduction in power generation. But our study differs from Alhajeri et al.[27] since we focus on the empirical aspect of the COVID-19 pandemic and renewable industry using a nonlinear framework, whereas the study of Alhajeri et al.[27] was more concerned with the qualitative aspect of this relationship. The nature of the COVID-19 pandemic and the induced restrictions is characterized by sudden and irregular jumps and linear dynamic is not suitable for capturing those jumps. Linear frameworks also cannot capture the asymmetric and complex dynamics between the variables [28]. Hence, not capturing the nonlinearity among the variables can lead to inconsistent outcomes with poorly behaved estimates and therefore, can easily undermine the objectives of this study [29]. Therefore, our study contributes to the empirical literature by employing several nonlinear estimation techniques such as Fourier ADL cointegration analysis by Banerjee et al. [30] and Markov Switching regression model of Hamilton [31] to capture the relationship among the variables.

The next section presents the data and methodology used to achieve the aims of the study. The empirical results are presented and discussed in section three while section four concludes the study with vital policy implications and suggestions.

## 2.0 Methodology and data description

### 2.1 Data description

The objective of this study is to analyze how the COVID-19 pandemic has affected renewable electricity generation in Denmark. In particular, we analyze how the overall electricity generation for the renewable sector (sum of biomass, hydropower, solar power, offshore wind, onshore wind, and other renewables electricity generation) has been affected due to the stringency index, economic support index, and COVID-19 daily confirmed deaths. The empirical model of the study is specified as follows:

$$REN_t = \beta_0 + \beta_1 SI_t + \beta_2 ESI_t + \beta_3 COVID_t + \varepsilon_t \quad (1)$$

Where $REN_t$ denotes the overall renewable electricity production of Denmark, $COVID_t$ indicates the daily confirmed deaths due to COVID-19, SI is the stringency index, ESI is the economic support index and $\varepsilon_t$ is the error term at time t.

We only transform the renewable electricity generation and COVID variables into natural logarithm and other variables remain in the level form since the other two variables are indices. These variables have been collected from different sources. For example, we use the daily death data for COVID-19 from the John Hopkins University database [32]. The stringency index and economic support index data come from the Oxford government response tracker database developed by Hale et al. [33]. The data for renewable electricity generation is sourced from the Energi data service developed by Energinet [34] of Denmark. This site provides the hourly data of renewable generation in Denmark. Since we do not have hourly data for any of our independent variables, we have taken the average of 24-hour electricity generation. The data period ranges from January to November 2020.

Stringency index implies the strictness of lockdown measures which mainly restrict human behaviour. This index incorporates closure of the school, public places and workplace closure, cancellation of public events, restrictions on gatherings, international travel and internal movement, and stay-at-home requirements. It ranges from 0 to 100, 100 being the harsh restrictions and lockdown policies implemented and 0 being no restrictions or lockdown. Denmark implemented one of the harsh lockdowns in Europe ever since the COVID-19 hit the country. Our initial hypothesis is that these policies have negatively affected the renewable sector. Thus the following hypothesis can be formulated:

**Hypothesis 1**: SI has a negative and significant impact on REN

The economic support index, on the other hand, also ranges from 0 to 100, where 100 means the country is fully supporting the people through income support or debt relief. COVID-19 has induced many countries to support the economy through measures such as fiscal stimulus and other monetary measures. So far, Denmark has announced a total stimulus package of $89,106 Million to tackle the pandemic, according to the Asian Development Bank [19], which is approximately 26% of its GDP. This package is composed of liquidity support, credit creation, direct long-term lending, equity support, and health and income support. This bulk amount of economic support to tackle the pandemic demonstrates that many of the climate 'projects' financing will get delayed, and support will be diverted away from clean energy projects to support the economy. Therefore, our second hypothesis argues that some of the funds (including those of renewable energy projects) that were aimed at tackling the climate crisis are diverted away from supporting the clean energy sector to prevent the immediate threat of COVID-19 [35]. Thus, the second hypothesis can be written as follows:

**Hypothesis 2**: ESI has a negative and significant impact on REN

The restrictions and lockdown implemented by the Danish government forced people to stay in their homes. As a result, the renewable sector suffered from proper maintenance and operation. Besides, the COVID variable (captured through the daily confirmed death of COVID-19) variable also incorporates the other two variables, such as SI and ESI. Therefore, it is expected that COVID will have a greater effect on the renewable sector than SI and ESI. Hence, our third and final hypothesis can be specified as follows:

**Hypothesis 3:** COVID has a negative and multiplier impact on REN

Descriptive statistics for the variables are presented in Table 1. As we have already mentioned, table 1 lists COVID and REN variables in logarithmic form and the other two variables in level form.

**Table 1. Descriptive Statistics**

| | COVID | ESI | REN | SI |
|---|---|---|---|---|
| Mean | 0.551603 | 80.48664 | 3.248134 | 55.73370 |
| Median | 0.173000 | 87.50000 | 3.249994 | 54.63000 |
| Maximum | 3.798000 | 100.0000 | 3.316353 | 72.22000 |
| Minimum | -1.036000 | 37.50000 | 3.146791 | 37.04000 |
| Std. Dev. | 0.755999 | 17.92189 | 0.035525 | 9.679303 |
| Skewness | 1.773064 | -1.776110 | -0.391970 | 0.184602 |
| Kurtosis | 5.948644 | 4.597531 | 2.642874 | 2.219191 |
| Jarque-Bera | 232.1923 | 165.6099 | 8.101258 | 8.143553 |
| Probability | 0.000000 | 0.000000 | 0.017411 | 0.017047 |
| Sum | 144.5200 | 21087.50 | 851.0111 | 14602.23 |
| Sum Sq. Dev. | 149.1704 | 83831.70 | 0.329384 | 24452.80 |
| Observations | 262 | 262 | 262 | 262 |

## 2.2 Methodology

### 2.2.1 Nonlinear dependence test

To examine the nonlinear dependence in the series of our model, we first employ the Brock-Dechert-Scheibkman (BDS) test provided by Brock et al. [36]. This test is used for model misspecification since it provides a high statistical power to determine the linearity or correct specification structure of the proposed model [37]. It is considered an important advancement in examining nonlinearity dependence when applied to pre-whitened data. It is based on correlation integral, an idea developed by Grassberger and Procaccia [38] to estimate the dimension of correlation. The performance of this test depends on the two parameters, one is ε (distance), and another one is d (value of the embedding dimension). It is expected that the distance between any pair of points can be equal to or less than ε under the assumption of independence [39].

### 2.2.2 Unit root test

To check the stationary of our variables, we have employed an Augmented Dicky Fuller test (ADF) and Fourier ADF unit root test. The general specification for the ADF test is as follows:

$$\Delta y_t = \alpha y_{t-1} + x_t \Upsilon + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} \dots . + \beta_p \Delta y_{t-p} + \nu_t \quad (2)$$

Where Δ is difference and $\alpha = \rho-1$ and ρ is the coefficient of the AR (ρ) process. $y_t$ is the variable under consideration and $v_t$ is white noise. The lagged term has been added to tackle the autocorrelation problem.

However, the traditional unit root tests such as ADF cannot capture the structural breaks. Our variables might have undergone some structural shifts, which further result in different forms of nonlinearity. Hence ADF test was again augmented for a nonlinear framework by Enders and Lee [40] where they used the Fourier function consisting of different frequencies. The following equation specifies a Fourier function:

$$Y(t) = \alpha_0 + \alpha_1 t + \sum_{j=1}^{m} \tau_j \sin\left(\frac{2\pi jt}{N}\right) + \sum_{j=1}^{m} \rho_j \cos\left(\frac{2\pi jt}{N}\right); m \leq \frac{N}{2}; t = 1,2 \quad (3)$$

Here, $\alpha_0$ and $\alpha_1$ are the intercept and trend coefficients. The amplitude and displacement dynamics of the Fourier function are indicated by $\tau_j$ and $\rho_j$. Also, we have N number of observations and m-optimal number of frequencies which will be determined by the information criteria, here j is Fourier frequency (values of j range from 1,2… to m). $\tau_j$ and $\rho_j$ are two nonlinear parameters in the above equation and if one of them is at least significant, this means that there is nonlinearity. However, the process will become linear if these parameters are zero.

### 2.2.3. Cointegration test

The essence of cointegration is to confirm whether the variables move together or not in the long run. Cointegration requires all the variables to be integrated in the same order. In this paper, we apply the Fourier ADL cointegration analysis suggested by Banerjee et al. [30] rather than Engle-Granger's [41] methodology or Johansen and Joselius [42] cointegration tests since they cannot capture the nonlinearity. This test does not require specifying the duration of the breaks as well as prevents power loss when too many dummies are used. The formula for this test is specified as follows:

$$\Delta y_{1t} = d(t) + \Theta_1 y_{1,t-1} + \pi y_{2,t-1} + \tau \Delta y_{2,t} + \varepsilon_t \quad (4)$$

Here, d(t) is the deterministic term and y, τ, and $y_{2t}$ is n*1 parameter vectors and explanatory variables.

The null hypothesis of this test is that of no cointegration. However, if the critical values developed by Banerjee et al. [30] are under the test statistic that is estimated, the null hypothesis will be rejected and cointegration will be confirmed.

### 2.2.4. Markov Switching Regression

Considering the possibility of nonlinearity and sudden change in the variability of a given indicator, here we employ a superior technique compared to other econometric models, which is the Markov Switching Regression model advocated by Hamilton [31]. This model provides a nonlinear alternative to linear models of Box Jenkins ARIMA or unobserved components models of Watson [43], Harvey and Todd [44], and Clark [45]. In this technique, the models are very flexible and can change against regime shifts. This test can be applied to non-stationary, dynamic, and linear cointegrated models. Hamilton [31] used the process provided by Goldfeld and Quandt [46] to determine the changes in the autoregressive 'process's parameters. According to Hamilton [31], the nonlinearities arise when the process experiences discrete shifts in regimes, this implies the episodes where the given series's dynamic behaviour is different.

The two regime Markov Switching regression can be written as follows:

$$X_t = \alpha_1 + \sum_{i=1}^{\rho} \Upsilon_{1,i} X_{t-i} + \alpha_{1,t} \text{ if } s_t = 1$$

$$X_t = \alpha_2 + \sum_{i=1}^{\rho} \Upsilon_{2,i} X_{t-i} + \alpha_{2,t} \text{ if } s_t = 2$$

Here, $\alpha_{i,t}$ is independently and identically distributed with mean 0 and variance $\sigma^2{}_i$. The state variable is donated by $s_t$, and it is governed by a first-order Markov chain. The transition probabilities of this state variable can be presented in the following matrix format:

$$P = \begin{matrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{matrix}$$

Here, if the value of $\rho_{ij}$ is small, the model will stay longer in state i. The duration of this state is expected to be $1/\rho_{ij}$. The regime numbers can be $r \geq 2$ [23].

2.2.5. Causality test

The cointegration test confirms whether there is any long-run relationship or not between two variables, but it does not say anything about the direction of causality. Granger causality is used to identify the direction of causality among the variables. Here, we employ Breitung and Candelon [47] frequency domain Granger causality test to examine the causal inference among the variables studied. Breitung and Candelon proposed a test which is based on sets of linear hypothesis on the autoregressive framework using a bivariate vector autoregressive (VAR) model. The framework developed by them can be used to disentangle long-run and short-run predictability. The superiority of this causality test over other traditional causality tests is that it permits the forecasting of variables examined at specific time frequencies. This will allow us to examine the changes where policy interventions can be provided, that is, whether in the short term, medium-term or long term [48].

## 3.0 Results and Discussions

As outlined in the methodology, as an initial technique, the BDS test of Brock et al. [36] is applied to capture nonlinearity in the time series variables. The outcomes of the BDS test for the variables of SI, ESI, REN and COVID in Denmark are reported in Table 2. The results provide empirical evidence that there is nonlinear behaviour in the time series variables.

**Table 2. BDS dependency test**

| | Dimension | BDS Statistic | z-Statistic | Prob. |
|---|---|---|---|---|
| SI | 2 | 0.182878 | 39.15713 | 0.0000 |
| | 3 | 0.319833 | 43.47282 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| | 4 | 0.412207 | 47.47358 | 0.0000 |
| | 5 | 0.473506 | 52.79388 | 0.0000 |
| | 6 | 0.516991 | 60.31391 | 0.0000 |
| ESI | 2 | 0.203520 | 22.27613 | 0.0000 |
| | 3 | 0.343580 | 23.64981 | 0.0000 |
| | 4 | 0.438894 | 25.32817 | 0.0000 |
| | 5 | 0.502749 | 27.77520 | 0.0000 |
| | 6 | 0.544551 | 31.11504 | 0.0000 |
| REN | 2 | 0.166786 | 46.90841 | 0.0000 |
| | 3 | 0.276761 | 48.96380 | 0.0000 |
| | 4 | 0.344884 | 51.24503 | 0.0000 |
| | 5 | 0.384711 | 54.86046 | 0.0000 |
| | 6 | 0.404865 | 59.89285 | 0.0000 |
| COVID | 2 | 0.119421 | 15.77295 | 0.0000 |
| | 3 | 0.218391 | 18.03169 | 0.0000 |
| | 4 | 0.285335 | 19.64285 | 0.0000 |
| | 5 | 0.338107 | 22.16545 | 0.0000 |
| | 6 | 0.368046 | 24.82805 | 0.0000 |

Note: *, **, and *** denote statistically significant at the 10%, 5% and 1%significance level.

We now proceed to estimate a linear unit root test, namely Augmented Dickey-Fuller (ADF), to examine whether the time series variables in the estimated models have a unit root. Moreover, we also employ the nonlinear unit root test, namely the Fourier-ADF (F-ADF) unit root test, which depends on the frequency and the lag length. F-ADF captures unknown structural breaks with frequencies to select the minimum sum of the squared residuals. The outcomes from these tests are reported in Table 3. As reported, at the 5% level, the time series variables have a unit root at the level. However, at the first difference, the variables are stationary. In other words, the variables are integrated into the same order or I(1).

| Table 3. ADF and Fourier ADF Unit Root Tests | | | |
|---|---|---|---|
| **ADF Unit Root Test** | | | |
| Variables | T-Statistic | Probability | |
| COVID | -2.4191 | *0.3688* | |
| ΔCOVID | -20.1264*** | *0.0000* | |
| ESI | -2.4735 | *0.3411* | |
| ΔESI | -16.1206*** | *0.0000* | |
| LREN | 3.3915* | *0.0547* | |
| ΔLREN | -14.3076*** | *0.0000* | |
| SI | -3.1852* | *0.0897* | |
| ΔSI | -16.0783*** | *0.0000* | |
| **Fourier ADF Unit Root Test** | | | |
| Variables | Frequency | F-Statistic | Fourier ADF Test Statistic |
| COVID | 1 | 8.010 | -4.257* |
| ΔCOVID | 1 | 1.091 | -5.606*** |
| ESI | 1 | 3.478 | -3.414 |
| ΔESI | 4 | 0.926 | -16.172*** |
| LREN | 5 | 2.321 | -3.421 |
| ΔLREN | 5 | 2.185 | -9.590*** |
| SI | 2 | 2.368 | -3.565 |
| ΔSI | 2 | 0.258 | -8.005*** |
| Critical values of Fourier ADF Test | | | |
| Frequency | 1% | 5% | 10% |
| 1 | −4.87 | −4.31 | −4.02 |
| 2 | −5.58 | −5.02 | −4.73 |
| 3 | −6.19 | −5.63 | −5.34 |

| | | | |
|---|---|---|---|
| 4 | −6.73 | −6.18 | −5.89 |
| 5 | -7.24 | −6.68 | −6.39 |
| Critical values of F | | | |
| | 10.35 | 7.58 | 6.35 |
| Note: Δ symbol indicates the first difference of the variables. *, **, and *** denote statistically significant at the 10%, 5%, and 1% significance level, respectively. The decisions are taken based on the 5% significance level. | | | |

As a next step, the present study applies the ADL cointegration test, which takes both nonlinearity and unknown structural breaks into account. The outcome from the ADL cointegration test is reported in Table 4. The null hypothesis of the ADL cointegration test is that there is no cointegration equation among the time series variables. The findings reveal that the null hypothesis can be rejected, imping that there is a long-run relationship between renewable electricity generation and stringent index, economic support index, and COVID-19 deaths in Denmark.

| **Table 4. Fourier ADL Cointegration Test** | | | |
|---|---|---|---|
| Model | Test Statistics | Frequency | Min AIC |
| REN=f (SI, ESI, COVID) | 5.142*** | 5 | -6.725 |
| | Critical Value | | |
| | 1% | 5% | 10% |
| | −5.08 | −4.38 | −4.01 |
| Note: *, **, and *** denote statistically significant at the 10%, 5%, and 1% significance level, respectively. | | | |

Since the present study captures the long-run linkage among the time series variables, we next explore the possible effect of the stringency index, economic support index, and COVID on renewable electricity generation employing Markov switching regression. The outcomes of the Markov switching regression are reported in Table 5. This test is a linear regression model with nonlinearities arising from discrete changes in regime. The present study undertakes two different regimes in the renewable electricity sector in Denmark, a high volatility regime (Regime 1) and low volatility regime (Regime 2).

**Table 5. Markov Switching Regression**

| Variable | Coefficient | Std. Error | z-Statistic | Probability |
|---|---|---|---|---|
| Regime 1 | | | | |
| SI | -0.0018** | 0.0009 | -2.0245 | 0.0429 |
| ESI | -0.0005* | 0.0003 | -1.7758 | 0.0758 |
| COVID | -0.0375** | 0.0095 | -3.9254 | 0.0001 |
| C | 3.4270*** | 0.0617 | 55.45868 | 0 |
| Regime 2 | | | | |
| SI | -0.0017*** | 0.0002 | -6.9143 | 0 |
| ESI | -0.0004*** | 0.0001 | -3.2837 | 0.001 |
| COVID | -0.0175*** | 0.0031 | -5.549 | 0 |
| C | 3.2862*** | 0.0195 | 167.7567 | 0 |

Note: *, **, and *** denote statistically significant at the 10%, 5%, and 1% significance level, respectively.

The outcomes in Table 5 show that the stringency index has a negative and significant effect on renewable electricity generation in Denmark in both regimes. The coefficients of the stringency index under both regimes are similar, indicating a similar effect of the lockdown on renewable electricity in high and low volatility periods. The negative effect of the stringency measures on renewable energy can be supported by the fact that the construction of renewable energy installations was delayed due to these measures implemented in the countries. These measures also disrupted the supply chain and directly impacted the commissioning of renewable electricity projects [49]. Also, many clean energy workers got unemployed due to the financial pressure of their respective companies [14]. For example, in Denmark, the Vestas which is the 'world's largest wind turbine manufacturer, cut jobs due to financial uncertainty associated with COVID-19. The company decided to shut down its projects of MHI Vestas and those in Lem Blade and Aarhus located in Denmark [50]. The IEA [51] reports that biofuel projects and utility-scale electricity may encounter delays in commissioning. The crisis severely hit the biofuel sector as the biofuel used drops due to restrictions of transport activity all around the country. The decrease in biofuel production will be 11.5%. Considering that Denmark's widely used energy source is bioenergy and COVID-19 has halted the production of many transport biofuel, our result is therefore not surprising.

In July 2020, European Union (EU) leaders, including that of Denmark, agreed about the recovery fund for coronavirus amounting to approximately 750 Billion Euro. This meant that a compromise had to be met regarding the climate budget. For example, cuts had to be made from the Just transition fund, a flagship of the European Commission aiming to assist carbon-intensive economics get rid of fossil fuels. Besides, funds were also cut from InvestEU (which helps meet the green goals of the member countries) and scientific research regarding the climate crisis [35, 52]. The aforementioned argument is reflected in our finding that the economic support index has significant negative impacts on renewable electricity. This segment of the finding falls in similar line with the findings from [39], who noted that financial or economic crisis could set back the target for reducing emissions as well as affect the deployment of renewable energies. These crises also happen to coincide with the commission of wind power projects. Since Denmark's electricity sources come mostly from the wind sector, our result that renewable energy was negatively affected by the pandemic is very reasonable.

Furthermore, we find that COVID significantly and negatively affects renewable electricity generation under both regimes. However, the high volatility regime's coefficient is greater than the coefficient under the low volatility regime, indicating that COVID has greater negative effects in the high volatility regime. The effects of COVID are also greater than that of stringency and economic support indices under both regimes. This segment of the result demonstrates the multiplier effect of the COVID pandemic, as proxied by the daily confirmed deaths, on renewable electricity. The increasing rate of COVID-19 death rate makes people afraid to go outside home and makes the government impose further strict regulations and lockdown. As a result, the COVID variable incorporates the impacts of the stringency index as well as that of fear of the employees and employers working in the renewable industry. The result can also be explained by the fact that many countries have experienced a total slowdown in the installation of distributed solar PV where the installation requires access to commercial buildings and houses. This segment of the result is consistent with Eroğlu [53], who noted that the renewable energy sector is getting affected severely because of lack of government support, issues related to the tax stock market, and supply chain delays that are caused by the pandemic.

To catch the causal impact of the stringent index, economic support index, and COVID-19 deaths on renewable electricity generation in Denmark at different frequencies, the present study implemented the BC causality test, which allows us to separate long-term causality from short-term causality. The BC causality test distinguishes nonlinearity and causal stages, whereas the test also encourages the identification of causality between parameters at various frequencies. The outcomes of the BC causality test are depicted in Table 6. We find that there is evidence of causality from SI to REN in the medium and short term, imping that the stringency index is an important predictor for renewable electricity generation in Denmark for the medium and short term. Moreover, COVID-19 deaths can also predict significant variation in renewable electricity generation in Denmark at different frequencies, specifically during the long and short term. However, we fail to capture any significant causality from the economic support index to renewable electricity generation in the long and short-terms.

**Table 6. BC Causality Test**

| | Long-term | | Medium-term | | Short-term | |
|---|---|---|---|---|---|---|
| Direction of causality | $w_i$=0.01 | $w_i$=0.05 | $w_i$=1.00 | $w_i$=1.50 | $w_i$=2.00 | $w_i$=2.50 |
| SI →REN | 2.754<br>(0.252) | 2.645<br>(0.266) | 6.651**<br>(0.035) | 16.806**<br>(0.000) | 23.919**<br>(0.000) | 33.760**<br>(0.000) |
| ESI →REN | 1.211<br>(0.545) | 1.126<br>(0.569) | 4.751*<br>(0.092) | 3.177<br>(0.204) | 0.208<br>(0.901) | 0.630<br>(0.729) |

| | | | | | | |
|---|---|---|---|---|---|---|
| COVID →REN | 5.471* | 5.511* | 2.217 | 2.383 | 5.982** | 5.310* |
| | (0.064) | (0.063) | (0.330) | (0.303) | (0.050) | (0.070) |

Note: <> and () stands for Wald test statistic and p-value, respectively. The path of causality is represented by→. 10%, %5, and 1% levels of significance are illustrated by *,** &***, correspondingly. SIC is used to verify the VAR model's lag lengths.

# 4.0 Conclusion and Policy Suggestions

## 4.1 Summary of Findings

The need to assess the impact of the COVID-19 outbreak on several parts of the economy cannot be overemphasized, with a special interest in the energy sector, which is one of those largely affected by the pandemic. As demonstrated by Eroğlu [53], renewable energy generation has been adversely affected due to uncertainty in the supply of materials, amongst others. Given the foregoing, this study presents a case for Denmark by investigating the impact of the COVID-19 pandemic on renewable electricity generation. To achieve this aim, data on renewable electricity alongside stringency index, economic support index, and COVID-19 daily confirmed deaths were collected and analyzed via a Markov Switching Regression and other pre-and post-estimation tests.

The result from the cointegration test first reveals that the variables are cointegrated, indicating that they have a long-run relationship with each other. To account for the high and low periods of uncertainty, we analyzed the relationship between COVID-19 and renewable electricity via a Markov switching regression model. Findings from this study reveal that both the stringency index and economic support index adversely influenced renewable energy generation in Denmark and the effect of these two measures was also similar in magnitude. However, the impact of the COVID-19 pandemic, proxied by the daily confirmed death, varied across two regimes, with having a higher effect in the high volatility period.

## 4.2 Policy Suggestions

Our findings are informative for energy policy during crisis events such as the COVID-19 pandemic and also during the post-crisis period. Regulations of economic activities amidst a disruption such as a pandemic require some flexibility. For example, issuing palliatives or forming a support bubble by the central government may improve the performance of vital supply chain initiatives needed for generating renewable energy. Also, there is no limit to the disturbances that creating economic support initiatives and workable models of compensation will cause to the energy sector in Denmark. Given that the energy sector is affected by the number of deaths and uncertainty during the pandemic, there is a need to move power guidelines towards a model that will advance productivity, decarbonization, as well as investment platforms that assume flexible returns.

Denmark's goal is to meet its 50% energy demand from renewable by 2030 and to become independent of fossil fuel by 2050. But as our analysis has shown, renewable energy is severely affected by the shocks arising from the pandemic. Therefore, while designing the policy frameworks for the post-COVID-19 period, several different measures need to be implemented by the government as delays and supply chain disruption in the renewable sector has occurred. Renewable technology adoption can resolve the post-COVID dilemma moments for Denmark. This requires strategic actions as the country continues to transition itself to the sources of clean energy in the post-COVID world. Investors are currently acting unstable due to the uncertainty associated with the renewable industry. The world's largest turbine manufacturer, Vestas, has already cut jobs owing to the financial pressure in Denmark. Therefore, the financial risks associated with renewables must be reduced so that investors do not shift away from renewable [54]. More support in the form of production and investment tax credit must be provided for clean energy investors.

The electricity sector of Denmark is highly reliant on wind farms, making it vulnerable to extreme events such as the pandemic. The country has to rely on its neighbouring countries to balance its renewable. For example, it has to import hydropower as the country is flat and has little opportunity of generating hydroelectricity itself. Furthermore, global accidents revolving around nuclear power plants have given rise to some prejudices regarding the development of nuclear energy in people's subconscious, including Denmark, where nuclear is banned since 1985. Yet, in terms of ensuring the environmental balance, nuclear power plants are considered to be one of the most reliable power source [55,56] Therefore, the incentives to boost the nuclear production in Denmark must come from the government as it will require changes in the perception of Danish people regarding nuclear power. . Also, instead of relying on neighbouring countries, the country can also target demand response, which decreases consumption to balance as has been noted by Martinot [57].

Compared to other countries, 'Denmark's transition to wind power from oil imported nation was done in a short period. Although this is laudable, there are concerns about whether generating electricity from new technology is higher than that of the old one. For Denmark, this seems to be very true. Different measures such as alignment of transmission, distribution, and competitive auctions should be implemented to reduce the cost of electricity, especially that of wind and solar. The high rates of energy taxation have also encouraged Danish consumers to switch towards their electricity generation, and this is a blow to the government as it is not cost-saving socio-economically. In this regard, a further decrease in heating taxation can be recommended. The country should also evaluate the solar heating policies with regards to a further extension of seasonal thermal storage. Furthermore, a more flexible district heating system should be encouraged, and tax levels should be adjusted to efficiently align the electricity and heating system.

### 4.3 Study Limitations and Future research scopes

Our study investigates how renewable generation can be affected by the COVID-19 pandemic. As such, we used three measures of the pandemic to assess their effects on the renewable sector. However, renewable electricity generation in Denmark is extremely affected by policy changes. Apart from the policy changes in terms of lockdown and economic support, our study could not incorporate any other benchmark policy variables. This is mainly because daily data for such policy variables are not yet available. It is possible to incorporate them in future studies when they become available for the COVID period of 2020. Also, Denmark has two price areas and the effect of the pandemic can vary across these two areas. Future studies may also explore impacts on these two price areas depending on the data availability.

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## Data availability

Data are available upon request from the corresponding author.

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