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Electricity Demand and CO Emissions during the COVID-19 Pandemic: The Case of India

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ABSTRACT

The present study examines the impact of electricity demand on CO emissions in the Indian economy using daily real-time data during the Covid-19 period. The subject was hardly addressed explicitly and quantitatively in environmental studies. Our study applied recently developed non-linear (asymmetric) autoregressive distributed lag (ARDL) and the Quantile ARDL techniques for analysis. The empirical findings confirm the existence of an asymmetric long-run relationship between electricity demand and CO emissions during the Covid-19 pandemic. Furthermore, the results reveal that the decrease (increase) in electric demand leads to a reduction (increase) in CO emissions in the long run. Besides, the results show that the increase in electricity demand generates more CO emissions in the short run. Our study will be helpful for policy-makers and regulators associated with energy and climate change amid the ongoing pandemic crisis and provide directions to the expected waves of pandemic scenarios.

Keywords: Electricity Demand, CO Emissions, Covid-19, Non-linear Autoregressive Distributed Lag Model, Quantile Autoregressive Distributed Lag Model, India
JEL Classifications: C32, I150, Q41, Q58

1. INTRODUCTION

Due to the spread of the Covid-19 pandemic, extreme limitations were enforced across the globe, and economic activities got effectively halted. The International Energy Agency (2020) report emphasized that the reduction in energy demand across the world during lockdown is due to the weakening of demand from the service and industry sectors. The energy demand began to increase due to ease of lockdown measures and resumed business activities. The Government of India imposed a strict lockdown from March 25, 2020, which was extended until May 30, 2020, with progressive changes in restrictions with time. In Figure 1, we can observe a significant drop in electricity demand during April 2020 and began to rise significantly in the preceding months and reverted to its growing path due to expansion in business activities. Moreover, the International Energy Agency (2020) report confirmed the recovery of electricity demand in India were at higher levels during the Covid-19 phase than in 2019 due to higher demand in industrial and commercial sectors and demand for irrigation. In this vein, Figure 1 reveals that the electricity demand in September and October 2020 was higher than the demand levels of September and October 2019 due to the ease of Covid-19 related restrictions and soaring economic activity.

In recent studies, Cheshmehzangi (2020), Edomah and Ndulue (2020), and Zhao et al. (2020) indicated that the Covid-19 pandemic could not be merely perceived as a critical factor for energy transition but rather as a significant disruption that could potentially have long-term effects on household energy consumption behavior and environment. Aruga (2020) showed that domestic household electricity consumption tends to increase during the lockdown. As work from home (WFH) became the new normal, several Indian firms had begun to engage and connect with employees and their families. These increased indoor human activities would increase electricity demand, which causes an increase in CO emissions. Therefore, Covid-19 paradoxically may have a detrimental effect on the air quality on the point. Moreover, the European Public Health Alliance (2020) report indicated that higher death rates for Covid-19 are linked to air quality in polluted cities.

During the recovery of emerging economies from the global financial crash in 2008, there was a sharp rebound in pollution levels. Likewise, it was observed from Figure 2 that electricity demand and CO emissions are gaining momentum in India at a steady phase during the Covid-19 as restrictions eased and business recouped. The preventing measures of Covid-19 in India, viz. working from home, staying home and staying safe social distancing, and refraining from outdoor activities, has forced people to involve in indoor activities. This led to increased electricity demand during the pandemic and produced high CO emissions. The key sources of indoor CO emissions include cloth dryers, water heaters, furnaces and boilers, induction stoves, electric ovens, grills, generators, power equipment, and lawn tools. These devices consume more electricity and produce high CO emissions. Furthermore, Raub et al. (2020) stated that power stations and industrial activities are vital sources of outdoor CO emissions generated into the atmosphere. The soaring industrial activities would increase electricity demand, which causes an increase in CO emissions.

Figure 1: Electricity Demand (MW)

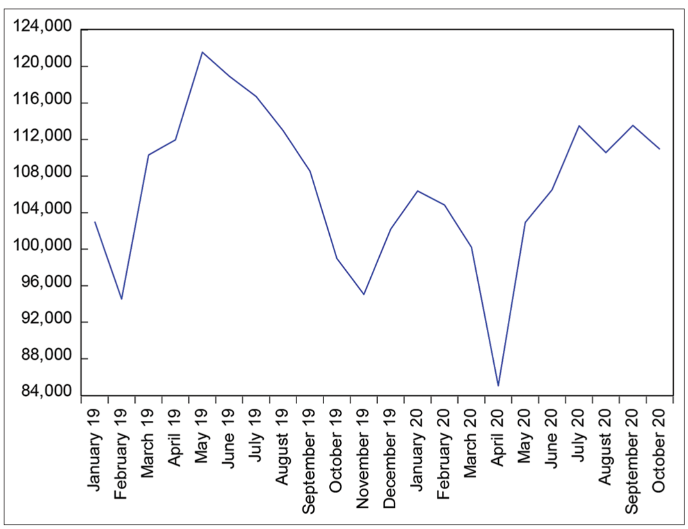


Figure 2: Electricity demand and CO emissions during Covid-19

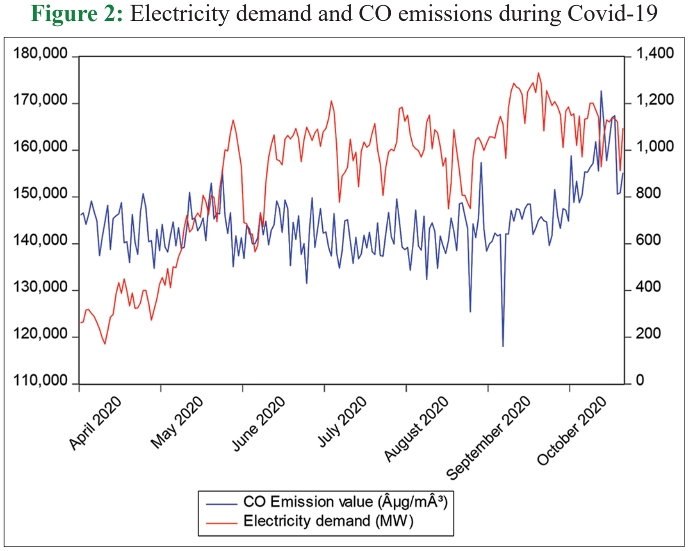
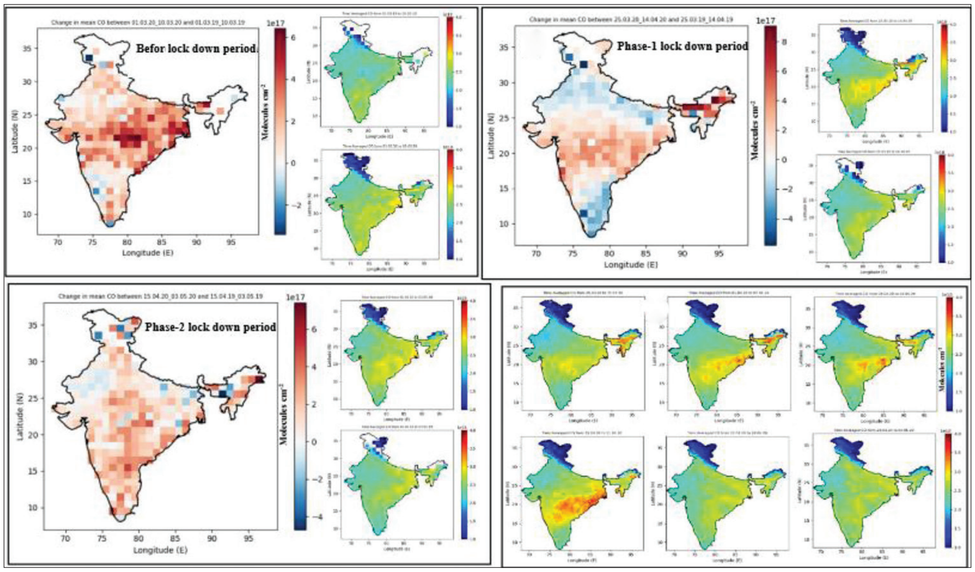


Figure 3 shows the average CO levels across Indian regions during the pre-lockdown period (May 2015-March 2020) and lockdown periods, viz. Phase 1 (25 March 2020-14 April 2020) and Phase 2 (15 April 2020-3 May 2020). The weekly variation in CO emission levels during the lockdown period is shown in Figure 3d. It was observed that there was a significant reduction in CO levels during Phase 1 across India compared to the Pre-lock-down period. The average CO levels are higher during the Phase 2 lockdown phase, and significant weekly variations in CO levels are observed during the lockdown phase. Therefore, it affects the most vulnerable people in the community, having respiratory and cardiovascular problems (Jain and Sharma, 2020). As soon as the businesses are permitted to resume their operations as indicated by the Government of India, the air quality is likely to start deteriorating in most cities, and by the time winters will approach, it may create the same conditions as it was in the year 2019. Pollution is inevitable due to a growing economy and results as one of the outcomes of the developing economies for moving towards industrialization. In addition, the increased electricity demand in India caused by averting behaviours that shift outdoor activities indoors in the later phase of the Covid-19 pandemic would lead to higher CO emissions. This causes environmental damage. Therefore, the present study examines the impact of electricity demand on CO emissions in the Indian economy using real-time data during the Covid-19 period. The subject was hardly addressed explicitly and quantitatively in the environmental studies and contributed on empirical grounds and serves as an essential reference for energy policy-making. Most of the existing literature applied cointegration and causality tests to examine the causal nexus between energy consumption, pollutants and economic activity in the context of developed and developed economies. These approaches not consider non-linearity and asymmetric effects in the time-series, hence biased towards the non-rejection of the null hypothesis. We employed advanced autoregressive distributed lag (ARDL) models taking into account the time series' structural breaks and asymmetric properties. The non-linear ARDL approach was applied to uncover short- and long-run asymmetries. Moreover, we extended the non-linear ARDL to a quantile framework, leading to a more prosperous new model, which allows testing for distributional asymmetry while accounting for short- and long-run asymmetries.

2. LITERATURE REVIEW

Magazzino (2014) examined the causal relationship between electricity demand, real per capita Gross Domestic Product (GDP) and total labour force in Italy and found that the GDP, labour force and electricity are negatively correlated in the long run. Moreover, there is a bi-directional Granger causality flow between real per capita GDP and electricity demand, while labor

Figure 3: CO concentration emissions



Source: Pathakoti et al. (2021)

force does not Granger cause neither real per capita GDP nor electricity demand. Magazzino (2017a) explored the stationary characteristics of electricity consumption in MENA countries from 1971 to 2013. The results illustrate that the electricity consumption is more uniform in GCC countries than in the other 11 countries. However, the six GCC countries have a higher converging rate on electricity usage than the other, implying this region is more integrated into the economic structure. Magazzino (2017b) examines the stationary properties of per capita energy use in the 19 Eurozone member countries using annual data from 1960–2013. They applied the Clemente et al. (1998) unit root test that determines structural breaks. Empirical results show that most of the country series does not reject the unit root null hypothesis at the 5% significance level both in the case of additive outlier and innovative outlier. Therefore, the authors suggest that shocks to per capita energy use are permanent. This result implies that following a significant structural change in the world oil market, per capita energy use will not return to its original equilibrium over a short amount of time. The results are particularly relevant since almost all Eurozone countries are net oil and gas importers. Mele and Magazzino (2021) investigated the causal nexus between the air pollutants, economic growth and COVID-19 deaths in India. The stationarity and Toda-Yamamoto causality tests were conducted using time series data from 1980 to 2018. According to their findings, the unidirectional direction was evidenced among the economic growth and pollution. Moreover, the study used data (January 29, 2020-May 18, 2020) on confirmed deaths (total and daily) and air pollution activity levels among 25 important cities in India. Using the Machine learning (ML) technique, the authors found a casual relation among PM2.5, CO_2, NO_2, and COVID-19 deaths using the ML technique. The findings support the hypothesis that a developing country's economic growth is bell-shaped.

Mitra et al. (2020) probed the level of CO_2 at 12 different locations in India during Pre- COVID (April 2019) and COVID period (April 2020). The analysis of variance test was used to compare the results of sub-sample periods. The CO_2 level dropped significantly during the lockdown phase and was found to be temporary. Becchetti et al. (2020) examined the linkages between the pollution levels, mortality and daily infections of COVID-19 provinces of Italy. The COVID-19 outbreak and death are due to the imprecise lockdown initiatives, the amount of local pollution and particularly non-digitalized activities, which were more resistant to closure during the pandemic crisis period. According to the study, COVID-19 infections were higher when the air pollution was higher, despite no causal nexus among the variables. Bao and Zhang (2020) studied the effect of lockdown on air pollution during COVID-19 in China. It is observed that the degree of the travel constraints impacted the air quality in 44 cities in northern China between January 1 and March 21, 2020. During the pandemic, the reduction in air pollution was strongly linked to travel limitations. Hence, understanding the importance of green production and consumption is vital. Magazzino et al. (2021) assessed the relationship between ICT connectivity, electricity usage, economic growth, and air pollution among 16 European countries (EU) during 1990-2017. The causality test results show a one-way causality between ICT use and electricity consumption, which leads to a rise in CO_2 emissions and GDP. Thus, the author suggests suitable measures to be taken to address ICT's adverse environmental effects. Shehzad et al. (2020) examined the effect of COVID-19 on carbon emissions in India from January to April 2020. The study reported a significant decrease in Nitrogen dioxide in major states and demonstrated that COVID-19 is considered a great evil in reducing air pollution in the Indian region.

Ghosh and Ghosh (2020) examined to measure air pollution during the lockdown period and infer its impact on the environment and health. Based on their findings, PM10, PM2.5, SO_2, and CO concentration levels decreased significantly. The leading cause of this reduction was due to traffic restrictions and the temporary closing of industrial plants. This resulted in improved climatic conditions, lower pollution, and reduced many seasonal diseases such as asthma and other respiratory problems. According to Gautam (2020), the COVID-19 had significant negative effects on society and the environment but showed had positive effects on air quality. The findings show that air quality in India has significantly improved. Jain and Sharma (2020) evaluated the influence of social distancing and travel restrictions in five Indian cities during the two phases (i.e. before and during lockdown). The results highlight that all major pollutants exhibited a significant decrease in all the cities except for ozone. The PM2.5, PM10, NO_2, CO, and O3 concentrations in March–April 2020 were lower than in March–April 2019. The study suggests that the government's top priority will be to revive the economy, which means it may forego the environmental benefits obtained during the lockdown. He et al. (2020) conducted a study among 4313 residential buildings and 17,422 commercial buildings in Arizona, United States and showed a significant positive correlation between the emission level and residential electricity consumption during the daytime. Moreover, the authors indicated that indoor activities lead to high CO concentration due to increased energy consumption. It is clear from the existing literature that there is a trade-off between nature and human activities, which is essential to analyze to make informed decisions. Therefore, considering the COVID-19 situation, we have examined the impact of electricity demand on CO emissions in the Indian economy and recommended policy measures to control the air quality in the economy in the coming future.

3. DATA AND METHODOLOGY

The Government of India took a key preventive measure by implementing a countrywide lockdown from March 25, 2020. Hence, the present study considers the COVID-19 pandemic period from March 25, 2020 to October 20, 2020. The daily real-time electricity demand data for the Indian economy was collected from the Power System Operation Corporation Ltd., a wholly-owned company of the Government of India under the Ministry of Power (https://posoco.in/reports/monthly-reports/monthly-reports-2020-21/). The study has measured the daily average Carbon Monoxide (CO) emissions in micrograms per cubic meter of air ($\mu g/m^3$) as a significant pollutant across the country, and data for the CO emission is obtained from openAQ (https://openaq.org/#/?_k=m9ez3d), which is a non-profit organization that collects air quality data across the globe.

The asymmetric ARDL and Quantile ARDL techniques are applied to examine the impact of electricity demand and CO emissions. The general form of the symmetric ARDL method proposed by Pesaran et al. (2001) takes the following form:

$$\Delta \ln CO_t = \alpha_o + \sum_{i=1}^{n} \alpha_1 \Delta \ln CO_{t-1} + \sum_{i=1}^{n} \alpha_2 \Delta \ln ED_{t-1} + \beta_1 \ln CO_{t-1} + \beta_2 \ln ED_{t-1} + \varepsilon_{1t} \tag{1}$$

where ln is the natural log and Δ is the first difference operator. ED and CO represent energy demand and carbon monoxide emissions, respectively. The long-run association between the proposed variables are examined using equation (1). As stated in Pesaran and Pesaran (1997), the F-statistic is used to test the existence of long-run relationship under the null hypothesis of no cointegration ($\beta_1 = \beta_2 = 0$) against the alternative hypothesis of the presence of cointegration ($\beta_1 \neq \beta_2 \neq \neq 0$), which is referred to as (F_{CO}|CO, ED). If the estimated F-statistic is higher than the upper bound of the critical value, there is a stable long-run relationship.

The ARDL specification of the error correction model is formulated as follows:

$$\Delta \ln CO_t = \alpha_o + \sum_{i=1}^{n} \alpha_1 \Delta \ln CO_{t-1} + \sum_{i=1}^{n} \alpha_2 \Delta \ln ED_{t-1} + \gamma_1 Z_{t-1} + \varepsilon_{1t} \tag{2}$$

In equation (2) above, γ_1 is the error correction term (ECT), and αs are the short-run parameters. The short-run effect is assessed based on the significance of the coefficients of each lagged regressor.

Shin et al. (2009) have recently developed the asymmetric ARDL model using negative and positive partial sum decompositions that allow identifying the asymmetric effect in the short run and long run. As the asymmetric ARDL approach extends the symmetric ARDL co-integration model, we incorporated the decomposed negative and positive series of exogenous variables to make the asymmetric ARDL specification.

$$\Delta \ln CO_t = \alpha_o + \sum_{i=1}^{n} \alpha_1 \Delta \ln CO_{t-1} + \sum_{i=1}^{n} \alpha_2 \Delta \ln ED^{+}_{t-1} + \sum_{i=1}^{n} \alpha_3 \Delta \ln ED^{-}_{t-1} + \beta_1 \ln CO_{t-1} + \beta_2 \ln ED^{+}_{t-1} + \beta_3 \ln ED^{-}_{t-1} + \varepsilon_{1t} \tag{3}$$

Cho et al. (2015) developed a dynamic quantile autoregressive distributed lag (QARDL) modelling approach that can concurrently capture both long-run and short-run relationships across a range of quantiles of the conditional distribution of the outcome variable in a fully parametric setting. The quantile counterpart of the equation (1), i.e., the QARDL model at τ^{th} quantile, is as follows:

$$\Delta \ln CO_t = \alpha_o(\tau) + \gamma_1 Z_{t-1}(\tau) + \sum_{i=1}^{n} \alpha_1(\tau) \Delta \ln CO_{t-1} + \sum_{i=1}^{n} \alpha_2(\tau) \Delta \ln ED_{t-1} + \beta_1(\tau) \ln CO_{t-1} + \beta_2(\tau) \ln ED_{t-1} + \varepsilon_{1t}(\tau) \tag{4}$$

The conditional long-run model for CO_t can be estimated by applying the ARDL approach, and reduced solution of equation (4) following the QARDL version of Cho et al. (2015) is as follows:

$$\ln CO_t = \lambda_1(\tau) + \lambda_2(\tau) \ln ED_{t-1} + v_1(\tau) \tag{5}$$

where $\lambda_2(\tau) = -\beta_2(\tau)/\beta_1$ and $v_1(\tau)$ is the random error.

Furthermore, the study applied the Breusch-Godfrey Serial Correlation Lagrange Multiplier test and Autoregressive Conditional Heteroscedasticity (ARCH) Lagrange Multiplier test to detect the autocorrelation and heteroscedasticity in the residuals of the estimated ARDL model.

Table 1: Descriptive statistics

	Energy demand (MW)	CO emission (Âμg/mÂ≥)
Mean	154319.6	683.485
Maximum	176568	1253.35
Minimum	118587	161.206
Skewness	−0.86465	0.84038
Kurtosis	2.54859	6.52054
Jarque-Bera	26.6192* (≤0.0001)	126.826* (≤0.0001)
Observations	200	200

*Significance at 1% level. CO: Carbon monoxide

Table 2: Nonlinearity tests

BDS test statistics		
Dimension (m)	**CO**	**ED**
2	0.034919* (5.5113)	0.183834* (31.6815)
3	0.053668* (5.3244)	0.314899* (34.0403)
4	0.058496* (4.8680)	0.404760* (36.6290)
5	0.056305* (4.49030)	0.464175* (40.1768)
6	0.048974* (4.0450)	0.502630* (44.9729)
Ramsey RESET test		
Lag	***F*-statistics**	**Probability**
1	20.37412*	≤0.0001
2	10.16542*	≤0.0001

*Significance at 1% level. m stands for the number of dimensions. BDS test statistics are calculated for the data series. Figures in parentheses *Z*-statistics. F-statistics under the Ramsey RESET test are calculated based on the residuals of the selected ARDL model with CO as a dependent variable. The null hypothesis is that the series are linearly distributed. ARDL: Autoregressive distributed lag, CO: Carbon Monoxide, BDS: Brock-Dechert-Scheinkman

Table 3: Bai–Perron multiple structural breaks test for CO

Break test	*F*-statistic	Critical value	Estimated break dates
0 versus 1	63.4944**	8.58	9/21/2020
1 versus 2	6.65937	10.13	6/18/2020, 9/09/2020
2 versus 3	1.09485	11.14	5/10/2020, 6/18/2020, 9/09/2020
3 versus 4	0.38170	11.83	5/10/2020, 6/18/2020, 8/17/2020, 9/21/2020
4 versus 5	0.00000	12.25	5/10/2020, 6/18/2020, 7/20/2020, 8/20/2020, 9/21/2020

**Significance at 5% level. The critical values are obtained from Bai and Perron (2003). CO: Carbon Monoxide

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The descriptive statistics are reported in Table 1. The average energy demand and CO emission during the study period are 154319.6 MW and 683.485 Âμg/mÂ³, respectively. The energy demand is negatively skewed, while CO emission is positively skewed. The kurtosis value for energy demand is <3, implying flat tails due to lesser outliers on either side. While the kurtosis value for CO emission is greater than three, indicating heavy tails on either side due to larger outliers. The significant Jarque-Bera statistics also show that both variables have deviated from the normal distribution.

4.2. Non-linearity Test

The time series are not normally distributed, resulting in less efficient linear estimates. For robustness, we performed the Brock-Dechert-Scheinkman (BDS) test and Ramsey RESET test to examine the nonlinearity properties of the time-series, and the results are presented in Table 2. The BDS test results reject the null of linearity in the time series at a 1% level of significance across all dimensions, and the Ramsey RESET test shows evidence of nonlinearity in the association between the two variables.

4.3. Structural Break Test

Besides, the study applied the Bai and Perron (2003) test of multiple structural breaks in the CO emission and detected a significant structural break on September 21, 2020 (Table 3). This was mainly because the Ministry of Health and Family Welfare, Government of India, released a Standard Operating Procedure for partial reopening schools from September 21, 2020 with the prescribed containment measures. This has facilitated partial reopening of schools in several cities in India, and parents will be encouraged to use their transport, and the procedures also extend to any transportation facilities provided by the schools. Moreover, the industrial activities resumed at all industrial estates with 100% workforce from September 21, 2020. Amid the protective residential indoor activities (WFH) and resumed outdoor economic activities might be directly attributable to a massive increase in CO emissions in major cities.

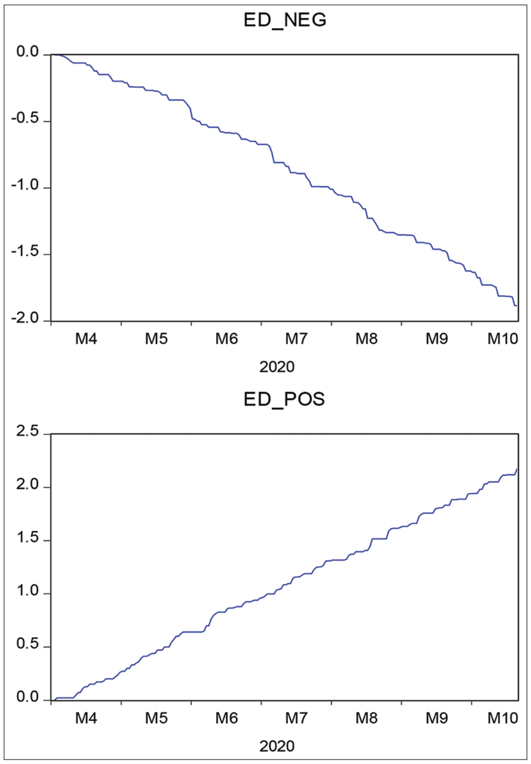
Taking into account nonlinearity and structural breaks in the time-series, we employ a non-linear (asymmetric) ARDL model to examine the effect of energy demand on CO emission during the COVID-19 phase. Moreover, the asymmetric ARDL model asserts that a particular economic variable has a differential impact

Table 4: Unit root tests

Panel A: ADF test statistics without structural break					
Variables	**Level**		**First difference**		**Order of integration**
CO	−6.064307* (≤0.0001)		-		I (0)
ED	−2.455525 (0.1281)		15.68528* (≤0.0001)		I (1)
Panel B: ZA test statistics with structural break					
Variables	**Level**	**Time break**	**First difference**	**Time break**	**Order of integration**
CO	−5.144157* (≤0.0001)	September 09, 2020	-	-	I (0)
ED	−5.288960** (0.0331)	May 05, 2020	-	-	I (0)

*and **Significance at 1% and 5% level, respectively. ADF: Augmented Dickey-Fuller, ZA: Zivot-Andrews, CO: Carbon Monoxide during positive and negative shocks [19]. Thus, the asymmetric ARDL method divides the energy demand into positive and negative components. Figure 4 represents the negative and positive components of energy demand during the study period.

Figure 4: Negative and positive components of energy demand



4.4. Unit Root Test

The order of integration is significant prior to perform the NARDL model and QARDL model. Both models are not applicable under the integration of order two, i.e., I(2). Thus, the unit root test assists in identifying the order of integration of the variables. We performed the Augmented Dickey-Fuller (ADF) test without structural breaks and Zivot and Andrews (2002) (ZA) unit root test that accounts for structural breaks in the dataset and the results are reported in Table 4. The ADF tests in Panel A depicts that the CO emission series is stationary at its level form I(0), while the energy demand series is stationary at its first difference I(I). Besides, the ZA test statistics depict that the parameters of their level form are stationary, i.e., I(0). The NARDL and QARDL models can be performed if the order of integration of the variables is the same, i.e., either I(0) or I(1) or a combination of both orders, i.e. I(0) and I(1). The evidence from the unit root tests allows us to perform the NARDL and QARDL models.

4.5. Asymmetric ARDL Test

Table 5 shows that the computed F-statistics for the asymmetric ARDL lie above the upper bound critical values at 1% significance level. Therefore, the rejection of the null hypothesis favours the asymmetric long-run relationship between the energy demand and CO emission during the COVID-19 phase.

Table 5: Asymmetric autoregressive distributed lag bounds test

Test-statistic	Value	K
F-statistic	10.92867*	2
Critical value bounds		
Significance (%)	**Lower bound**	**Upper bound**
10	2.63	3.35
5	3.10	3.87
2.5	3.55	4.38
1	4.13	5

*Significance at 1% level. The critical values are determined from Shin et al. (2009). K is the number of regressors in the equation. The optimum lag length is determined based on the SIC. SIC: Schwarz Information Criterion

The long-run and short-run estimates of the asymmetric ARDL model are depicted in Table 6. From the long-run estimates in Panel A, we observe that the partial sum of negative changes in energy demand has a negative and significant effect on CO emissions during the study period, while the partial sum of positive changes in energy demand has a negative and insignificant impact on CO emissions. Examining negative changes in energy demand indicate that a one-unit decrease in energy demand negatively affects the country's CO emissions, causing a decrease in CO emissions of about 0.795 units.

The short-run estimates in Panel B show that a partial sum of positive changes in energy demand has a positive and significant

Table 6: Asymmetric autoregressive distributed lag estimates

Variables	Coefficient	SE	*t*-Statistic	Probability
Panel A: Long-run estimates				
ED^+	−0.604071	0.394922	−1.529596	0.1278
ED^-	−0.795300***	0.452564	−1.757320	0.0805
C	6.321090*	0.107480	58.81171	≤0.0001
Panel B: Short-run estimates				
Variables	**Coefficient**	**SE**	***t*-statistic**	**Probability**
ΔCO_{t-1}	−0.206544*	0.070278	−2.938944	0.0037
ΔED_t^+	1.216735***	0.675809	1.800413	0.0734
ΔED_t^-	−0.173860	0.698101	−0.249047	0.8036
ECT_{t-1}	−0.526725*	0.079047	−6.663431	≤0.0001
Diagnostic checks				
Breusch-Godfrey Serial Correlation LM test			1.289790 (0.2778)	
ARCH-LM test			0.012437 (0.9113)	

*and ***Significance at 1%, 5% and 10% level, respectively. The optimum lag length is determined based on the SIC. SIC: Schwarz Information Criterion, SE: Standard error, CO: Carbon Monoxide, ECT: Error correction term, ARCH-LM: Autoregressive conditional heteroscedasticity lagrange multiplier

Table 7: Estimated QARDL model

Quantiles (τ)	$\alpha_o(\tau)$	$\alpha_{2ED}(\tau)$	$\gamma_1 Z_{t-1}(\tau)$	$\lambda_1(\tau)$	$\lambda_2(\tau)$
0.10	−0.1651* (0.0178)	−0.2394 (0.7236)	−0.9320** (0.4383)	2.5152 (2.2438)	0.0381 (0.1394)
0.20	−0.1112* (0.0154)	−0.5300 (0.6406)	−0.8767** (0.3849)	2.9373 (2.3593)	−0.0169 (0.1797)
0.30	−0.0736* (0.0149)	−0.6292 (0.5897)	−0.6683*** (0.3988)	1.5462 (2.2892)	0.1512 (0.1721)
0.40	−0.0224* (0.0132)	−0.1479 (0.5268)	−0.5885** (0.2925)	2.2481 (1.9488)	0.0398 (0.1527)
0.50	0.01777 (0.0139)	−0.1802 (0.5228)	−0.8249* (0.3101)	2.1532 (1.8225)	0.0890 (0.1436)
0.60	0.0468* (0.0138)	−0.0945 (0.4982)	−0.6749* (0.2543)	2.2883 (1.6343)	0.0751 (0.1287)
0.70	0.0826* (0.0135)	−0.1760 (0.4409)	−0.8591* (0.2239)	2.7792*** (1.4312)	0.0571 (0.1179)
0.80	0.1281* (0.0149)	0.0887 (0.5116)	−0.9250* (0.1741)	1.1163 (1.4552)	0.1770 (0.1225)
0.90	0.1818* (0.0158)	−0.4214 (0.6484)	−0.8664* (0.1302)	−0.0846 (1.5614)	0.2645*** (0.1420)

*.** and *** denotes significance at 1%, 5% and 10% level, respectively. The values in parentheses indicate standard errors. The optimum lag length is determined based on the SIC. SIC: Schwarz Information Criterion, QARDL: Quantile autoregressive distributed lag

effect on CO emissions, while a partial sum of negative changes in energy demand has a negative and insignificant impact on CO emissions. The positive changes in energy demand indicate that a 1% increase in energy demand positively affects the country's CO emissions, causing the increase in CO emissions by about 1.216%. Besides, the coefficient of ECT is negative and statistically significant at the 1% level of significance, implying that nearly 52% of the short-run deviation within the CO emissions are corrected and converged back to equilibrium in the long run. The table results show that the insignificant test statistics of the Breusch-Godfrey Serial Correlation LM test and ARCH-LM test imply that the residuals of the estimated asymmetric model are free from the autocorrelation and heteroscedasticity problems, respectively.

4.6. Quantile ARDL Test

Setting τ = 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, we estimated QARDL method for robustness check and the results are reported in Table 7. The QARDL estimates show that the speed of adjustment parameters (γ_1) is statistically significant with the expected negative sign at all quantiles, indicating a reversion to the long-term equilibrium relationship between energy demand and CO emission during the Covid-19 phase. It is evident from the table results that $\lambda_{2(ED)}$ is statistically significant at the highest quantile, indicating a positive asymmetric relationship between energy demand and CO emissions. This implies that an increase in energy demand leads to a rise in CO emissions in the long-term. Besides, the short-term results show that α_{2ED} it is statistically insignificant across the quantiles, implying that energy demand does not significantly influence CO emissions.

We plot the estimation results in Appendix 1, which displays the quantile estimates of the short-term and long-term parameters with 90% confidence intervals with quantiles ranging from 0.05 to 0.95. Following Feng et al. (2011) and Cho et al. (2015), we employed the wild bootstrap procedure for the confidence intervals because bootstrapping can offer enhanced estimates of the underlying sampling distribution than the asymptotic theory. The quantile estimates of the ECT start with a 52% adjustment speed at low quantiles and reach toward maximum convergence to the long-run equilibrium as the quantile increases. This confirms the long-run association between energy demand and CO emissions. Besides, the quantile estimate of the long-run energy demand remains at similar levels until τ = 0.80 and reaches a peak of 4% at the highest quantile, τ = 0.95. This suggests the evidence of the asymmetric effect of energy demand on CO emissions and confirms a long-term positive impact of energy demand on CO emissions. Moreover, the quantile estimates of the short-term energy demand parameter $\lambda(\tau)$ are negligibly small across all quantiles, ranging between -2 and 1. This suggests that a change in energy demand would not give rise to a noticeable and immediate change in CO emissions.

5. CONCLUSIONS

The Indian economy was not an exception to the highly infected Covid-19 cases, and the government had imposed severe stay-at-home restrictions. The electricity demand in India increased intensely amid the pandemic, and consequently, the CO emissions level was recorded high due to increased indoor human activities and resumed industrial activities. This might have adverse effects on air quality. Our study attempted to examine the impact of electricity demand on CO emissions in the Indian economy using daily real-time data during the Covid-19 period. The subject was hardly addressed explicitly and quantitatively in environmental studies. Our study applied recently developed non-linear (asymmetric) ARDL and the Quantile ARDL techniques for the analysis. The empirical findings confirm the existence of an asymmetric long-run relationship between electricity demand and CO emissions during the Covid-19 pandemic. Furthermore, the results reveal that the decrease (increase) in electric demand leads to a reduction (increase) in CO emissions in the long run. Besides, the results show that the increase in electric demand generates more CO emissions in the short run.

The recovery of electricity demand driven by industrial and commercial sector activities and increased demand from the household sector due to continued indoor activities increased the CO emissions during the Covid-19 forced confinement. Therefore, policy-makers concerned about environmental issues should adopt more sensible and dynamic strategies to promote the necessity of renewable and sustainable energy investments. The study demands immediate strategies from the power sector to excel their efficiency in response to the increased demand for electricity during the Covid-19 pandemic. Consequently, more efforts are needed to implement programs for consumer education for conserving energy and its associated benefits of preserving our environment.

Most importantly, the policymakers should focus on the transition from fossil fuel-based energy systems to renewable and cleaner energy alternatives, stringent emissions control measures and awareness on practical usage of electricity in the cities to have a clean and breathable environment in the future.

The asymmetric effects of electricity demand from different sectors on environmental quality might be further analyzed for future research. Moreover, research examining the asymmetric linkages between electricity demand and air pollutants in developing and developed economies could illuminate the potential and problems in financing clean energy investments.

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APPENDIX

Appendix 1: Quantile process estimates