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Believe It Or Not: Covid 19 Environmental Effects Are More Negatives Than Positives

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Abstract

In addition to altering drastically people's daily lives, Covid 19 has slowed down economic activities, imposed restrictions, and enforced lockdown, altogether causing significant effects on the environment. Studying the direction, magnitude, and durability of these effects carries a serious lesson for the whole world. Preliminarily evidence suggests that Covid 19 has temporarily improved air quality, reduced greenhouse gas emissions, and noise pollution, yet, due to lock-down, the flourishing of delivery services has pulled up the single-use plastics, increased the usages of vehicles by a lower ratio of passengers/vehicle, and raised demand for energy. Using the approach of the Ambiental Kuznets curve, we investigate the impact of Covid 19 total cases on the monthly average of carbon monoxide emissions measured in micrograms per cubic across a sample of developed, heavy polluters, economies from 2014 to 2020. Driscoll-Kraay regressions confirm the Covid-19 long-run polluting impact by increasing monoxide emissions in countries of analysis.

Keywords: COVID 19, Environment, Monoxide emissions, Driscoll-Kraay regressions

Introduction

COVID-19 has had a considerable impact on the world economy, people's livelihoods, and the environment. Mixed evidence has been portrayed in the recent literature regarding the environmental effects of Covid 19. Based on the European Environmental Agency data, COVID-19 lockdown, perceptions slowdown of economic activities resulted in short termed dropdown in Co2 emissions in many European cities, such as Barcelona, Madrid, Milan, Rome, and Paris (EEA, 2020). Other studies have highlighted the dramatic surge in global demand for personal protective equipment (PPE) such as masks, gloves, gowns, bottled hand sanitizer, single-use plastic packaging. The production, consumption, and disposal of these products have increased environmental threats. Most of the existing evidence is based on organizational reports, empirical evidence about the linkages between the pandemic and the environment is still deficient. There are different sides of environmental pollution; noise, air, chemicals, urban life, yet this study investigate the impact of Covid 19 total cases on the monthly average of carbon monoxide emissions measured in micrograms per cubic across a sample of developed, heavy polluters, economies from 2014 to 2020. Driscoll-Kraay regressions confirm the Covid-19 long-run polluting impact by increasing monoxide emissions in countries of analysis.

Some studies have postulated that the pandemic has improved air quality, decreased Greenhouse Gas (GHGs) emissions, and minimizing water and noise pollution due to the shrunk touristic travels and consumption of transport (Le Quéré et al., 2020). On contrary, other studies highlighted that during the pandemic, CO_2 levels have increased in some regions, attributing this to the heavy transport and mobilization of the medical staff and food delivery services. Most of the studies apply a comparative pre-post approach to analyse the environmental effects of Covid 19 by studying its impact on some air gas pollutants such as carbon monoxide (CO), nitrogen oxides (NO and NO_2), carbon dioxide (CO_2), and particulate matter (PM_{10} and $PM_{2.5}$). We summarize the key findings of several recent studies in Table 1, wherein those studies that studied the nexus between COVID-19 pandemic and CO_2 emissions at the city or provincial level are presented in part A of the table. While those studies that have studied the environmental impact of the pandemic and enforced lockdown at countries level are presented in part B.

Table 1. Summary of literature review

Authors	Sample	Key findings
A. Studies focusing on COVID-19 outbreak and air quality (CO_2 emissions) in city level		

Tian et al. (2021)	Eight Canadian Cities	The impact of COVID-19 pandemic on CO_2 emission concentration in the atmosphere is significant in each city.
Gao et al. (2021)	Chinese megacities	COVID-19 epidemic improves air quality.
Han et al. (2021)	Xi'an, China	COVID-19 pandemic enhances the quality of air.
Prats et al. (2021)	Barcelona, Spain	A negative relationship is observed between COVID-19 pandemic and air pollution.
Hashim et al. (2021)	Baghdad, Iraq	COVID-19 helps in air quality and natural environment.
Borhani et al. (2021)	Tehran, Iran	COVID-19 pandemic helped reduce CO_2 emission.
Magazzino et al. (2020)	Three French Cities	A direct relationship between COVID-19 pandemic and air pollution have been found.
Mitra et al. (2020)	Kolkata City, India	COVID-19 epidemic lowers CO_2 emission.
Tello-Leal and Macías-Hernández (2020)	Victorio, Mexico	A positive correlation exists between COVID-19 pandemic and CO_2 emission.
Bashir et al. (2020)	New York City, USA	Air quality is significantly linked to changes in the COVID-19 epidemic.
Zhang et al. (2020)	219 Chinese cities	Air pollution is positively associated with COVID-19 cases.
Andrée (2020)	355 Municipalities, Netherlands	Pollution concentration has a positive influence on the confirmed COVID-19 cases.
Rahman et al. (2020)	Dhaka City, Bangladesh	COVID-19 outbreak plays an important role in air pollution.
Zoran et al. (2020)	Milan, Italy	COVID-19 epidemic was having a positive role in air pollution reduction.
Nakada and Urban (2020)	São Paulo State, Brazil	COVID-19 pandemic has a positive impact on air quality.

Hutter et al. (2020)	Vienna, Austria	An adverse association between air pollution and COVID-19 was deduced.
Otmani et al. (2020)	Salé City, Morocco	A significant reduction in emissions was observed during the COVID-19 pandemic.
Kerimray et al. (2020)	Almaty, Kazakhstan	COVID-19 outbreak and air pollution are strongly correlated each other.
Mahato et al. (2020)	Delhi, India	COVID-19 pandemic is significsntly improved air quality.
B. Studies focusing on COVID-19 outbreak and air quality (CO_2 emissions) in country level		
Filonchyk et al. (2021)	Poland	The connection between COVID-19 outbreak and air quality has been found positively.
Islam et al. (2021)	Bangladesh	COVID-19 reduces atmospheric pollutants.
Jephcote et al. (2021)	United Kingdom	COVID-19 infection increases air quality.
Gama et al. (2020)	Portugal	Air quality improved during the pandemic.
Iqbal et al. (2020)	Pakistan	COVID-19 pandemic lead to a negative impact on CO_2 emission.
Mele and Magazzino (2020)	India	COVID-19 outbreak and CO_2 emission is directly connected each other.
Yusup et al. (2020)	China, USA, Europe and India	A negative connection exists between COVID-19 pandemic and atmospheric CO_2 concentration.
Zu et al. (2020)	China	Positive and significant relationship between COVID-19 and CO_2 emission were found.
Zambrano-Monserrate et al. (2020)	China, USA, Italy, and Spain	Both positive and negative indirect impact of COVID-19 on air quality were observed.
Berman and Ebisu (2020)	USA	COVID-19 pandemic declines air pollution.

Methodology

Using the approach of the Ambiental Kuznets curve (Grossman & Krueger, 1993: Dasgupta et al., 2002) which specifies the relationship between contamination and economic growth, we will opt for a similar, yet slightly modified version where we select as dependent variable the monthly average of carbon monoxide emissions measured in micrograms per cubic meter of air µg/m³ using the information of the Air Quality Open Data Platform -AQOP- (2021). To observe the relationship with the pandemic, we use the monthly sums of the cases of Covid-19 by country using the information of the European Centre for Disease Prevention and Control -ECDPC- (2021). To serve this purpose the model is specified as:

$$CO_{it} = \alpha + \beta_1 EAI_{it} + \beta_2 EAI_{it}^2 + \sum_{m=1}^{k} \gamma_m x_{m_{i,t}} + \delta_1 Cov_{it} + e_{it} \tag{1}$$

Where CO_{it} is the monthly average carbon monoxide emissions of country i at month t, the monthly economic activity index by country EAI_{it}, it's square form EAI_{it}^2 to capture marginal effects, and a set of x covariates available (see for detail the variables by country in Appendix A) for the same monthly periodicity, in which we selected the unemployment rate, the inflation (considering the consumer price index by country) and the inclusion of the Covid-19 variable of total cases Cov. Sample is considered between December of 2014 to November of 2020 given the availability of the data. From specification (1), different estimations will take place by cumulatively adding the set of covariates and examining the change in the statistical significance and the parameters.

$$CO_{it} = \alpha + \beta_1 EAI_{it} + \beta_2 EAI_{it}^2 + \delta_1 Cov_{it} + e_{it} \tag{1.1}$$

$$CO_{it} = \alpha + \beta_1 EAI_{it} + \beta_2 EAI_{it}^2 + \gamma_1 UE_{it} + \delta_1 Cov_{it} + e_{it} \tag{1.2}$$

$$CO_{it} = \alpha + \beta_1 EAI_{it} + \beta_2 EAI_{it}^2 + \gamma_1 UE_{it} + \gamma_2 CPI_{it} + \delta_1 Cov_{it} + e_{it} \tag{1.3}$$

Preliminary unit-root analysis (Appendix B) confirms that the order of integration of the variables is I(1) for the carbon monoxide emissions, economic activity indexes, and the total cases of Covid-19, meanwhile the covariates of unemployment and inflation also follows an I(1) process, converting expression (1) in a static approximation for the long-run. In order to obtain robust statistical inferences for the model, and to avoid a spurious regression under the context of the imbalanced panel data, Kao's (1999) residual-based tests are performed, where the result indicates the evidence of cointegration between the variables (all sets of covariates included). To account for serial correlation, cross-sectional dependency and heteroskedasticity in the results, we use the approach of robust standard errors for panel data regression proposed by Driscoll & Kraay (1998). Error Correction Models using an extended Engle & Granger approach to panel data are also estimated using the long-run information for these specification in order to proceed with short-run analysis.

The countries of analysis involve the top largest economies (the criteria for this classification are derived from the World's bank ranking by GDP) as the next table specifies.

Table 2. World Bank's ranking of Economies by GDP

Code	*Country*
US	United States
JP	Japan
DE	Germany
IN	India
GB	United Kingdom
FR	France
IT	Italy
BR	Brazil
CA	Canada

Note: Due to the lack of information from multiple variables of China, it was excluded from this selection.
Source: World Bank (2019).

Data Description

The principal sources of information for the research uses monthly data from the Federal Reserve Bank of ST. Lous -FRED- (2021), Centre for Monitoring Indian Economy -CMIE- (2021), and the World Bank (2020) (see Appendix A for details).

Table 3. Global Statistics of the Sample

Variable	Type	Mean	Std. Dev.	Min	Max	Observations
Carbon Monoxide Emissions	overall	2.688421	2.518964	.1	15.5081	N = 350
	between		2.507587	.2211501	7.696009	n = 8
	within		1.142907	-.0210413	14.63398	T-bar = 43.75
EAI	overall	99.61086	2.615567	77.18473	101.6701	N = 370
	between		.2556287	99.31522	100.0532	n = 8
	within		2.604763	77.37624	101.7994	T-bar = 46.25
Total cases Covid-19	overall	1447869	2915884	0	1.37e+07	N = 40
	between		1557607	58588.5	4375949	n = 8
	within		2457659	-2928054	1.07e+07	T-bar = 5.0
UE	overall	7.076216	3.426713	2.2	23.5	N = 370
	between		3.068415	2.828261	10.86122	n = 8
	within		1.838434	.6851051	23.06622	T-bar = 46.25
CPI	overall	104.3565	6.641746	94.19368	132.101	N = 370
	between		5.408438	100.6913	114.3719	n = 8
	within		4.488136	86.50099	122.0857	T-bar = 46.25

Source: Own Elaboration (2021).

The average carbon monoxide emissions are 2.69 micrograms per cubic meter of air µg/m³, while the Economic Activity Index in average has a value of 99.61, indicating that for the sample between 2014 and 2020 the trend is downwards than the unity for the indexes in the countries of analysis. Total cases of Covid-19 on the other hand have been growing exponentially reflecting an average of 1'447,869 of people infected monthly, the unemployment rate in average is 7.07% and the inflation measured by the consumer price index has been growing up reflecting an average value of 104.36 in the inflation index.

Table 4. Country Level Statistics

ID	Statistic	CO	EAI	Total Cases of Covid-19	UE	CPI
Brazil	Obs	44	45	3	45	45
	Mean	4.265455	99.48158	1474374	10.69111	112.0492
	Min	1.9	92.65543	2	4.3	94.19368
	Max	6.79	101.6701	3908272	13.7	124.3005
	sd	1.176121	1.714598	2123478	2.764123	8.564535
Canada	Obs	45	48	4	48	48
	Mean	1.473005	99.60543	151243.5	6.645833	103.0026
	Min	0.8821429	87.0349	20	5.4	98.40528
	Max	2.2	101.2002	381557	13.7	107.8535
	sd	0.282125	2.22515	163073.9	1.337982	2.737043
Germany	Obs	45	47	5	47	47
	Mean	0.2422295	99.58878	314002.2	3.887234	102.5219
	Min	0.1	89.42888	79	3	98.51642
	Max	1.081818	101.1058	1069912	4.9	106.2177
	sd	0.2884813	2.051226	433142.1	0.5877803	2.377384
France	Obs	45	47	5	47	47
	Mean	1.485436	99.41934	557822.8	9.331915	102.0274
	Min	0.1	77.18473	5	6.8	98.86
	Max	2.878947	101.0142	2276874	10.5	105.09
	sd	0.9012723	3.630418	970559	0.8790079	1.964058
India	Obs	36	40	7	40	40
	Mean	7.696009	99.31522	2813148	7.51	114.3719
	Min	4.986547	80.22737	0	3.4	102.1358
	Max	11.91111	101.2744	9462809	23.5	132.101
	sd	1.654087	4.272225	3822284	3.836919	9.137763
Italy	Obs	45	49	6	49	49
	Mean	0.2211501	99.45953	390912.2	10.86122	101.4179
	Min	0.1	85.04956	2	8.7	99.34884
	Max	0.8228682	101.0073	1601554	12.5	103.5
	sd	0.2109211	2.927137	605432.8	1.031143	1.337516
Japan	Obs	45	46	4	46	46
	Mean	3.598105	100.0532	58588.5	2.828261	100.6913

	Min	1.969231	92.01619	245	2.2	99.4
	Max	5.770513	101.1165	148962	3.6	102.3
	sd	0.7244478	1.455526	66877.74	0.419345	0.8868987
United States	Obs	45	48	6	48	48
	Mean	3.562537	99.92356	4375949	4.877083	100.7417
	Min	2.25684	92.01619	25	3.5	99.4
	Max	15.5081	101.1165	1.37E+07	13.3	102.3
	sd	2.299613	1.619505	5146680	1.740046	0.901496

Note: Sample from January of 2014 to November of 2020. Source: Own Elaboration (2021).

The country-level statistics report that Japan is the country with the higher average value in the Economic Activity Index shared with the higher average in carbon monoxide emissions followed by the U.S. in both aspects. The Covid-19 total cases are superior for the U.S. in comparison to the rest of the countries, and the countries with the highest unemployment rate and inflation are respectively Italy and India.

Empirical Results

Multiple models have been estimated using the specification of (1) and separated by the individual inclusion of the covariates in each estimation maintaining the structure focused in the Economic Activity Index and Covid-19 total cases, the regression outputs of the specifications (1.1), (1.2), and (1.3) can be located in Appendix C. The first estimation only contained the relationship between the carbon monoxide emissions, the economic activity index (and its squared form) with the total cases of Covid-19. Regarding the statistical significance of the relationships analyzed, the economic activity index and its square form are significant at a 95% level of confidence to explain the behaviour of the carbon monoxide emissions, the Covid-19 variable of total cases is significant at a 99% level of confidence. It is estimated that the parameter of the linear term of the economic activity index β_1 is negative, with a value of -2.65, meanwhile, the parameter associated with the nonlinear term β_2 of the economic activity index is positive with a value of 0.14, this result establishes that over increments of the economic activity indexes in average it will tend to increase greatly the carbon monoxide emissions, contrary to the Kuznets theory. On the other hand, Covid-19 cases are positively correlated with the carbon emissions with a positive parameter for δ_1 which in this first estimation is around $3.1e^{-07}$.

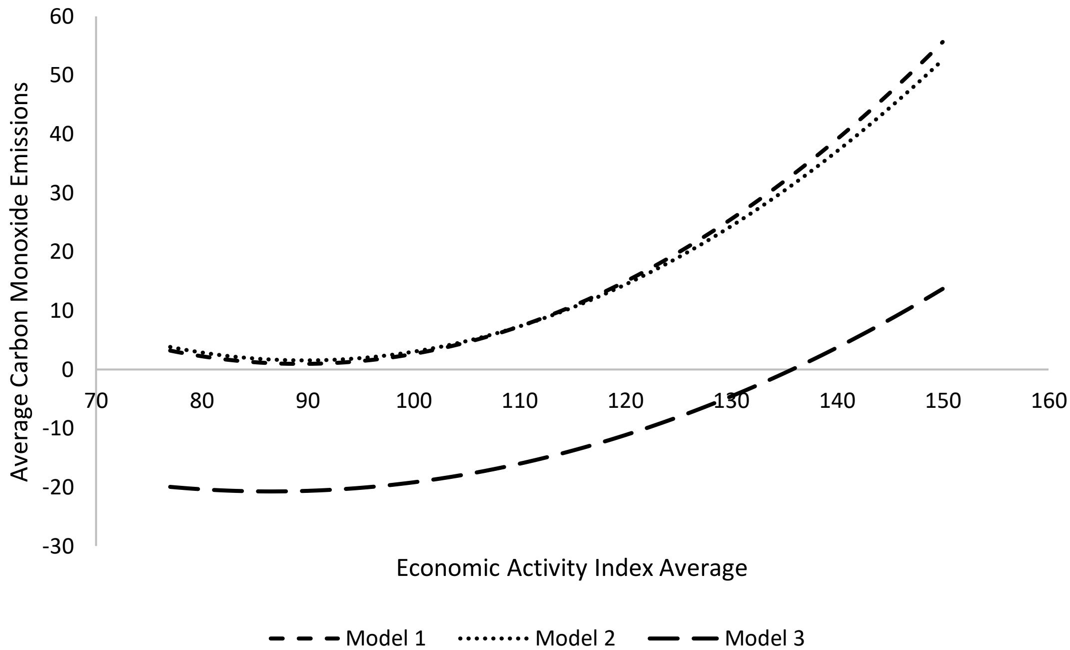
The second estimation including the economic activity index and the covariate of unemployment rate derives similar results, except that the unemployment rate is not statistically significant to explain the carbon monoxide emissions. The economic activity index and its square form are both significant under a 95% level of confidence, with values for the parameters of -2.52 and .014 for the linear β_1 and nonlinear term β_2 respectively. The Covid-19 variable is significant with a 99% level of confidence, with an average effect of $3.05e^{-07}$ in the carbon monoxide emissions.

The third estimation includes all the variables involving the set of covariates, such as economic activity index, unemployment rate, inflation (measured by the consumer price index), and the Covid-19 total cases. This estimation gives similar evidence of the overall results regarding the statistical significance of the variables, under a 90% level of confidence the economic activity index is significant to explain the carbon monoxide emissions, but the magnitude is estimated from -1.4 in the linear term and 0.008 in the quadratic term. The unemployment rate is statistically significant with a level of 99% of confidence to explain the carbon monoxide emissions, the estimated parameter is -.21 indicating an inverse relationship. The inflation is significant at a 99% level of confidence to explain the carbon emissions, and it's positively correlated with an estimated parameter of 0.22, meanwhile, the Covid-19 variable beholds the same statistical significance result with a 99% level of confidence, positively correlated with the carbon emissions but with an impact of $1.48e^{-07}$.

It is noted that across these estimations when an increase of the total cases of Covid-19 in average by country overtime occurs, there's an increase of carbon monoxide emissions, this result is statistically significant with a 99% level of confidence, but it has to be interpreted with special caution since the causality of carbon emissions cannot be explained merely by the Economic Activity Index, Unemployment, Inflation and Covid-19 phenomena, yet these variables were common across countries and with a monthly periodicity allowing to develop this research. There might be causal paths where the pandemic increased the emissions as the estimations reflect, for example, an increase in the total cases of a country can lead to higher amounts of energy consumption, which might lead to increases in the demand of energy, therefore, higher emissions of pollutants might result from this aspect, or in another approach, not only the cases would lead to an increase in the energy consumption, also it would tend to avoid public transportations and increase the usages of vehicles by a lower ratio of passengers/vehicle, this could be speculated as a potential source of emissions as consequences of the pandemic.

Overall, across the estimated specifications, the results remain robust regarding the statistical significance of the regressors, and for our special interest, the economic activity index and the total cases of Covid-19 are significantly correlated with the carbon monoxide emissions. The estimated behavior of the Ambiental Kuznets curve across the models using the carbon emissions and the economic activity index in average are depicted in the next graph:

Graph 1. Carbon Monoxide Emissions and Economic Activity: Linear projections of the estimated models.



Source: Own Elaboration (2021).

Concerning the short-run analysis (see Table A6 in Appendix C), there's no evidence that Covid-19 cases are significant to explain the monthly changes in the carbon monoxide, this result is consistent across specifications where we cannot reject the alternative hypothesis that the parameter associated to the new cases with a 95% level of significance. This implies that there's no statistical evidence to suggest that there are short-run dynamics influencing the behavior of the carbon monoxide emissions. The error correction terms of each short-run model are significant in overall with a 90% level of confidence, these terms are negative, between 0 a 1, suggesting stable long-run relationships captured in specifications (1.1), (1.2) and (1.3).

Conclusion

After examining the short and long-run environmental effects of Covid 19, in particular by tracing the advances in carbon monoxide emissions in a selected group of heavy polluters, developed countries. Using the approach of the Ambiental Kuznets curve, we find robust empirical evidence on the long-term polluting effects of Covid 19. Across the different specifications, an increase in the total cases of Covid 19 leads to higher amounts of energy consumption, which might lead to increases in the energy demand, as consequence higher polluting emissions. The enforced lockdown and social safety measures, pushing people to avoid public transportations and increase the usages of vehicles by a lower ratio of passengers/vehicle, this could be speculated as a potential source of emissions as consequences of the pandemic. Concerning the short-run analysis, there's no evidence that Covid-19 cases are significant to explain the monthly changes in the carbon monoxide. Some evidence in the literature suggests that Covid 19, in the short run, has improved air quality and reduced water pollution in several countries. As Covid 19 restrictions started to loosen and some economic activity has returned, governments need to consider the interconnected and cohesive dynamics between the economy, environment, and social safety systems, while sketching the ways out of the pandemic.

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APPENDIX A

Table A1. A detailed list of variables by class of indicators and source.

Country	ID variable	Name of indicator	Class of Indicator	Source
US	1	Coincident Economic Activity Index for the United States	Economic Activity Indicator	https://fred.stlouisfed.org/series/USPHCI
US	2	Consumer Price Index for All Urban Consumers: All Items in the U.S. City Average	Inflation Index	https://fred.stlouisfed.org/series/CPIAUCSL
US	3	Unemployment Rate for the United States	Unemployment Rate	https://fred.stlouisfed.org/series/M0892AUSM156SNBR
US	4	Population	Population	https://fred.stlouisfed.org/series/POPTHM
CHINA	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for China	Economic Activity Indicator	https://fred.stlouisfed.org/series/CHNLORSGPNOSTSAM
CHINA	2	Consumer Price Index CHINA	Inflation Index	https://fred.stlouisfed.org/searchresults/?st=China%20unemployment
CHINA	3	The Urban Surveyed Unemployment Rate(%)	Unemployment Rate	https://data.stats.gov.cn/english/easyquery.htm?cn=A01
JAPAN	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for Japan	Economic Activity Indicator	https://fred.stlouisfed.org/series/JPNLORSGPNOSTSAM
JAPAN	2	Consumer Price Index of All Items in Japan	Inflation Index	https://fred.stlouisfed.org/series/JPNCPIALLMINMEI
JAPAN	3	Unemployment Rate of JAPAN	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTJPM156S
JAPAN	4	Active Population: Aged 15-64: All Persons for Japan	Population	https://fred.stlouisfed.org/series/LFAC64TTJPM647S
GERMANY	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP)	Economic Activity Indicator	https://fred.stlouisfed.org/series/DEULORSGPNOSTSAM
GERMANY	2	Consumer Price Index of All Items in Germany	Inflation Index	https://fred.stlouisfed.org/series/DEUCPIALLMINMEI
GERMANY	3	Harmonized Unemployment Rate: Total: All Persons for Germany	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTDEM156S
INDIA	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for India	Economic Activity Indicator	https://fred.stlouisfed.org/series/INDLORSGPNOSTSAM
INDIA	2	Consumer Price Index: All Items for India	Inflation Index	https://fred.stlouisfed.org/series/INDCPIALLMINMEI
INDIA	3	Unemployment Rate Monthly time series (%): India	Unemployment Rate	https://unemploymentinindia.cmie.com/

UK	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for the United Kingdom	Economic Activity Indicator	https://fred.stlouisfed.org/series/GBRLORSGPNOSTSAM
UK	2	Consumer Price Index of All Items in the United Kingdom	Inflation Index	https://fred.stlouisfed.org/series/GBRCPIALLMINMEI
UK	3	Harmonized Unemployment Rate: Total: All Persons for the United Kingdom	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTGBM156S
FRANCE	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalized for France	Economic Activity Indicator	https://fred.stlouisfed.org/series/FRALORSGPNOSTSAM
FRANCE	2	Consumer Price Index of All Items in France	Inflation Index	https://fred.stlouisfed.org/series/FRACPIALLMINMEI
FRANCE	3	Harmonized Unemployment Rate: Total: All Persons for France	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTFRM156S
ITALY	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalised for Italy	Economic Activity Indicator	https://fred.stlouisfed.org/series/ITALORSGPNOSTSAM
ITALY	2	Consumer Price Index of All Items in Italy	Inflation Index	https://fred.stlouisfed.org/series/ITACPIALLMINMEI
ITALY	3	Harmonized Unemployment Rate: Total: All Persons for Italy	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTITM156S
BRAZIL	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalised for Brazil	Economic Activity Indicator	https://fred.stlouisfed.org/series/BRALORSGPNOSTSAM
BRAZIL	2	Consumer Price Index: All Items for Brazi	Inflation Index	https://fred.stlouisfed.org/series/BRACPIALLMINMEI
BRAZIL	3	Brazil Unemployment Rate	Unemployment Rate	https://www.investing.com/economic-calendar/brazilian-unemployment-rate-411
CANADA	1	Leading Indicators OECD: Reference series: Gross Domestic Product (GDP): Normalised for Canada	Economic Activity Indicator	https://fred.stlouisfed.org/series/CANLORSGPNOSTSAM
CANADA	2	Consumer Price Index: Total, All Items for Canada	Inflation Index	https://fred.stlouisfed.org/series/CPALCY01CAM661N
CANADA	3	Harmonized Unemployment Rate: Total: All Persons for Canada	Unemployment Rate	https://fred.stlouisfed.org/series/LRHUTTTTCAM156S

Note: The table contains all the name of the variables used for the regression analysis all-in monthly periodicity. It is noted that China was deleted from the analysis due to the lack of information in these variables and missing observations in the same period of time of the analysis. Source. Own Elaboration (2021).

APPENDIX B.

Table A2. Fisher-type unit-root Augmented Dickey-Fuller tests.

Variable	Test		Statistic	p-value	Decision
Carbon Monoxide Emissions	Inverse chi-squared (16)	P	37.3621	0.0019	Non-stationary
	Inverse normal	Z	-0.9406	0.1735	
	Inverse logit t(44)	L	-1.5602	0.0629	
	Modified inv. chi-squared	Pm	3.7763	0.0001	
Difference Carbon Monoxide Emissions	Inverse chi-squared (16)	P	235.6623	0.0000	Stationary
	Inverse normal	Z	-13.7895	0.0000	
	Inverse logit t(44)	L	-23.2399	0.0000	
	Modified inv. chi-squared	Pm	38.8312	0.0001	
Economic Activity Index	Inverse chi-squared (16)	P	17.7918	0.3362	Non-stationary
	Inverse normal	Z	-0.4904	0.3119	
	Inverse logit t(44)	L	-0.3157	0.3769	
	Modified inv. chi-squared	Pm	0.3167	0.3757	
Difference Economic Activity Index	Inverse chi-squared (16)	P	163.6871	0.0000	Stationary
	Inverse normal	Z	-8.9081	0.0000	
	Inverse logit t(44)	L	-15.7094	0.0000	
	Modified inv. chi-squared	Pm	26.1076	0.0001	
UE Rate	Inverse chi-squared (16)	P	19.1750	0.2597	Non-stationary
	Inverse normal	Z	0.8982	0.8155	
	Inverse logit t(44)	L	1.3833	0.9132	
	Modified inv. chi-squared	Pm	0.5613	0.2873	
Difference UE Rate	Inverse chi-squared (16)	P	77.5003	0.0000	Stationary
	Inverse normal	Z	-6.2331	0.0000	
	Inverse logit t(44)	L	-7.5568	0.0000	
	Modified inv. chi-squared	Pm	10.8718	0.0000	
Inflation Rate (CPI)	Inverse chi-squared (16)	P	13.4181	0.6420	Non-Stationary
	Inverse normal	Z	1.7303	0.9582	
	Inverse logit t(44)	L	1.8419	0.9639	
	Modified inv. chi-squared	Pm	-0.4564	0.6760	
Difference Inflation Rate (CPI)	Inverse chi-squared (16)	P	80.8997	0.0000	Stationary
	Inverse normal	Z	-6.2567	0.0000	
	Inverse logit t(44)	L	-7.6386	0.0000	
	Modified inv. chi-squared	Pm	11.4728	0.0000	
Total Cases Covid-19	Inverse chi-squared (16)	P	0.0000	1.0000	Non-Stationary
	Inverse normal	Z	.	-	
	Inverse logit t(44)	L	.	-	
	Modified inv. chi-squared	Pm	-2.8284	0.9977	
Difference New Total Cases Covid-19	Inverse chi-squared (16)	P	144.1746	0.0000	Stationary
	Inverse normal	Z	-11.4917	0.0000	
	Inverse logit t(44)	L	-29.2507	0.0000	
	Modified inv. chi-squared	Pm	22.6583	0.0000	

Note: Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. Newey–West automatic bandwidth selection and Bartlett kernel. Automatic lag length selection based on SIC. Ho: All panels contain unit roots, Ha: At least one panel is stationary, Autoregressive parameter: Panel-specific. Source: Own elaborations (2021).

Table A4. Kao Residual tests of Cointegration.

Test for cointegration	Statistic	p-value
Modified Dickey-Fuller t	.	.
Dickey-Fuller t	.	.
Augmented Dickey-Fuller t	.	.
Unadjusted modified Dickey Fuller t	3.5566	0.0002
Unadjusted Dickey-Fuller t	4.5371	0.0000

Note: Same cointegrating vector for the tests, Panel means included, Autoregressive parameter same for all test. Lags: 2.63 (Newey-West), Bartlett's kernel selection. Ho: No cointegration, Ha: All panels are cointegrated. Source: Own Elaboration (2021).

APPENDIX C.

Table A5. Long-run Driscoll-Kraay Regressions

Specification	1.1	1.2	1.3
Model	1	2	3
Variables	CO	CO	CO
EAI	-2.654**	-2.524**	-1.479*
	(0.929)	(0.824)	(0.693)
EAI^2	0.0149**	0.0141**	0.00854*
	(0.00508)	(0.00448)	(0.00379)
UE		-0.0543	-0.208***
		(0.0327)	(0.0326)
CPI			0.223***
			(0.0295)
$Cov-19$	3.10e-07***	3.05e-07***	1.48e-07***
	(2.96e-08)	(2.81e-08)	(3.78e-08)
Time Effects	No	No	Yes
Root MSE	2.4949	2.4922	2.1864
Prob > F	0.0000	0.0000	0.0000
Constant	119.5**	114.8**	43.26
	(42.08)	(37.68)	(32.69)
Observations	350	350	350
R-squared	0.027	0.032	0.262
Number of groups	8	8	8

Note: Driscoll-Kraay estimator was selected using the lag length specification from Hoechle (2007). Computations are done with Stata 16, Source. Own elaboration (2021).

Table A6. Short-run Driscoll-Kraay Regressions

ECM Specification	1.1	1.2	1.3
Model	ECM (1)	ECM (2)	ECM (3)
Variables	ΔCO	ΔCO	ΔCO
ΔEAI	44.69	42.17	48.60
	(57.94)	(58.08)	(58.14)
ΔEAI^2	-0.226	-0.214	-0.246
	(0.291)	(0.292)	(0.292)
ΔUE		0.136	0.112
		(0.113)	(0.113)
ΔCPI			-0.0385
			(0.112)
ΔCov	0	0	0
	(0)	(0)	(0)
e_{it-1} (1.3)			-0.0719*
			(0.0371)
e_{it-1} (1.2)		-0.0638**	
		(0.0241)	
e_{it-1} (1.1)	-0.0628**		
	(0.0248)		
Constant	-0.0711	-0.0696	-0.0364
	(0.0390)	(0.0390)	(0.0538)
Time Effects	No	No	Yes
Root MSE	0.7624	0.763	0.7651
Prob > F	0.0052	0.0094	0.0198
Observations	272	272	272
R-squared	0.047	0.049	0.051
Number of groups	8	8	8

Note: Lagged values of the long-run equation are specified with parenthesis, where e_{it-1} (1.1) are the lagged residuals of the static (1.1) equation, e_{it-1} (1.2) are the lagged residuals of (1.2) specification, and e_{it-1} (1.3) are the lagged residuals of specification (1.3). Driscoll-Kraay estimator was selected using the lag length specification from Hoechle (2007). Computations are done with Stata 16, Source. Own elaboration (2021).