

Panel Cointegration Modelling of COVID-19 Monthly Infected Cases and Deaths

A. Rajarathinam* and J. B. Anju

Department of Statistics, Manonmaniam Sundaranar University, Tirunelveli – 627 012, Tamil Nadu State, India

Received: 21 Sep. 2021, Revised: 12 Jan. 2022, Accepted: 18 Feb. 2022

Published online: 1 Mar. 2022

Abstract: In this paper, the cointegration relationships between COVID-19 new infection cases and the number of deaths due to COVID-19 in all 37 districts of Tamil Nadu state, India, during the period from July 3, 2020 to March 31, 2021 are investigated based on a panel regression Fully Modified Least Squares method and the Granger causality test.

Keywords: Cointegration, Fully Modified Least Squares, Granger Causality Test, Panel Regression Model, Pedroni and Kao unit roots tests

1 Introduction

1.1 Study background

Since the first suspected case of coronavirus disease-2019 (COVID-19) was noted on December 1, 2019, in Wuhan, Hubei Province, China, a total of 40,235 confirmed cases and 909 deaths have been reported in China (as of February 10, 2020), evoking fear locally and internationally [1]. The COVID-19 pandemic has affected most of the world's economies and has led to a large number of deaths. In the absence of antiviral drugs and vaccines, the number of new COVID-19 infections has increased tremendously and has caused many deaths. The deployment of various methodologies to analyse pandemic data has become an especially important research area with respect to forecasting new coronavirus infection cases and deaths.

1.2 Study objectives

This paper aims to study the cointegration relationships between the number of COVID-19 new infection cases and the number of deaths due to COVID-19 in all 37 districts of Tamil Nadu state, India, during the period 3rd July 2020 to 31st March 2021 based on a panel regression model with the number of deaths (DEATH) due to COVID-19 as the dependent variable and the number of

new positive COVID-19 infection cases (NCASE) as the independent variable.

1.3 Review of Methodological Literature

[2] employed panel unit root and panel cointegration techniques to estimate the long- and short-run income and price elasticities of the residential demand for electricity in G7 countries. Their panel results indicate that in the long run, residential demand for electricity is price elastic and income inelastic. The study concludes that from an environmental perspective, there is a potential to use pricing policies in the G7 countries to curtail residential electricity demand and thus curb carbon emissions in the long run.

[3] used panel cointegration data estimation techniques to examine the impact of trade on energy consumption in a sample of 8 Middle Eastern countries for the period 1980 to 2007. Short-run dynamics show Granger causality from exports to energy consumption and a bidirectional feedback relationship between imports and energy consumption. Long-run elasticities estimated from FMOLS show that a 1% increase in per capita exports increases per capita energy consumption by 0.11%, while a one per cent increase in per capita imports increases per capita energy consumption by 0.04%. These results are important because they establish that increased trade affects energy demand in the Middle East in both

* Corresponding author e-mail: rajarathinam@msuniv.ac.in

the short and long run. This finding has implications for energy policy and environmental policy.

[4] applied panel unit root tests, panel cointegration methods and panel causality tests to investigate the relationship between EC, GDP and CO₂ emissions for 15 MENA countries for the annual period 1973-2008. The findings of this study reveal that there is no causal link between GDP and EC or between CO₂ emissions and EC in the short run. However, in the long term, there is a unidirectional causality running from GDP and CO₂ emissions to EC. In addition, to address heterogeneity among countries and endogeneity bias in regressors, this paper applies the FMOLS and the DOLS approaches, respectively, to estimate the long-run relationship between the three factors.

[5] analysed the demand for electricity and provided out-of-sample forecasting at the sectoral level using a panel cointegration approach. The econometric model permits cross-sectional heterogeneity within a dynamic framework that incorporates information on relevant income and prices of domestic and foreign goods. Both the short-run dynamics and the long-run slope coefficients were allowed to vary across cross-sections. Additionally, testing for unit roots and cointegration in panels allows for heterogeneous fixed effects and deterministic trends. Using Egyptian data, it is shown that the empirical model produces reliable ex post forecasts near the end of the full sample period. These pseudo forecasts are representative of what one would expect if the forecasting relationship were stationary. The long-run parameter estimates are then used to conduct ex-ante forecasting under plausible assumptions for policy-making.

[6] investigated the short- and long-term cointegration relationships between the cumulative number of new cases of COVID-19 infection (X) and the cumulative numbers of deaths due to COVID-19 (Y). In addition, they investigated the long-run equilibrium relationship between these variables using an autoregressive distributed lag model and bounds cointegration tests. The stability of the estimated model was also assessed. The cumulative sum of recursive residuals test and the cumulative sum of recursive residuals squares tests were used to assess the consistency of the model parameters.

[7] assessed the dynamic relationship between the number of newly infected COVID-19 cases and the number of deaths due to COVID-19 using the Johansen-Fisher cointegration test, a vector error correction model and the Granger causality test. The daily numbers of newly infected COVID-19 cases and daily deaths due to COVID-19 in the United States, Canada, Ukraine and India were collected from websites for the period from 01-04-2020 to 26-12-2020. The summary statistics revealed that the highest numbers of COVID-19 infection cases were registered in the United States, followed by India, Canada and Ukraine. The highest number of deaths due to COVID-19 were registered in the United States, followed by India, Ukraine and Canada. The death percentage was exceedingly high in Canada,

followed by the United States, Ukraine and India. The Johansen-Fisher cointegration test results revealed the existence of one cointegration equation. The vector error correction model and Granger causality test revealed that long- and short-term causality occurred between COVID-19 infection and death cases. The speed of adjustment was found to be 9.9%.

2 MATERIALS AND METHODS

2.1 Materials

The COVID-19 dataset was collected from the official Tamil Nadu government website (www.stopcorona.tn.gov.in) from 3rd July 2020 to 31st March 2021 (the study period). Various econometric tools related to panel data regression modelling were employed to investigate the research questions of the study. Several methodologies for panel data regression modelling are discussed in the methods section. EViews Ver. 11. was used for the calculations.

2.2 Methods

2.2.1 Panel data model

Panel data are a type of data that contain observations of multiple phenomena collected over different time periods for the same group of individuals, units, or entities. In short, econometric panel data are multidimensional data collected over a given period. A simple panel data regression model is specified as follows:

$$Y_{it} = \alpha + \beta X_{it} + v_{it} \quad (1)$$

where $v_{it} = \gamma_i V_{i(t-1)} + \mu_{it}$ are the estimated residuals from the panel regression analysis. Here, Y is the dependent variable, X is the independent or explanatory variable, α and β are the intercept and slope, respectively, i stands for the i^{th} cross-sectional unit and t for the t^{th} month. In addition, X is assumed to be nonstochastic and the error term to follow the classical assumptions, namely, $E(v_{it}) = N(0, \sigma^2)$. In this study, i, that is, the number of cross-sections (districts), is 37 ($i=1, 2, 3, \dots, 37$), and $t=1, 2, 3, \dots, 9$.

Detailed discussions of panel data modelling can be found in [8], [9] and [10]. By combining time series of cross-sections of observations, panel data provide “more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency”.

2.3 Unit root tests

Unit roots in panel data can be tested using the [11] test or the [12] Lagrange multiplier (LM) stationarity test. The

null hypothesis is that the panels contain unit roots, while the alternative hypothesis is that the panels are stationary. In the results, if the p value is less than 0.05, one can reject the null hypothesis and accept the alternative hypothesis.

2.4 Panel cointegration test

In our model, if the study variables DEATH and NCASE contain a panel unit root, one should test whether there is a long-run equilibrium relationship between the study variables. We use the [13] test to determine whether the panel cointegration allows heterogeneity in the intercepts and slopes of the cointegrating equation. In his test, [13] provides seven statistics with which to test the null hypothesis, the latter referring to no cointegration in heterogeneous panels. One of the seven statistics is termed the “within dimension”. It considers common time factors and allows for heterogeneity across countries. Another statistic is termed the “between dimension” and allows for heterogeneity of parameters across countries. The seven statistics established by [13] are as follows:

- (1) Within dimension (panel tests):
 - Panel v -statistics
 - Panel Phillips–Perron type r-statistics.
 - Panel Phillips–Perron type t-statistic.
 - Panel augmented Dickey-Fuller (ADF) type t-statistics.
- (2) Between dimension (group tests):
 - Group Phillips–Perron type r-statistics.
 - Group Phillips–Perron type t-statistic.
 - Group ADF type t-statistic.

These seven statistics are based on the estimated residuals from the estimated panel regression Eq. (1) as used by [13]. In this panel regression, the null hypothesis tested whether the cointegration is equal to unity. [13] tabulated the finite sample distribution for the seven statistics using Monte Carlo simulations. If the test statistics exceeded critical values determined by Pedroni, the null hypothesis of no cointegration was rejected, implying that a long-run relationship exists between the study variables [14].

2.5 Fully Modified Least Square Regression

The fully modified least squares regression (FMOLS) regression was originally designed by [15] to provide optimal estimates of cointegrating regressions. The method modifies least squares to account for serial correlation effects and for the endogeneity in the regressors that results from the existence of a cointegrating relationship. The fully modified OLS principles can accommodate considerable heterogeneity across individual members of the panel. Additionally, this method enables researchers to selectively pool the

long-run information contained in the panel while permitting the short-run dynamics and fixed effects to be heterogeneous among different members of the panel.

2.6 Testing for causality [16]

The causal relationship between two stationary series X_t and Y_t can be assessed based on the following bivariate autoregression:

$$X_t = \phi_0 + \sum_{k=1}^p \phi_k Y_{t-k} + \sum_{k=1}^p \phi_k X_{t-k} + v_{it} \quad (2)$$

and

$$Y_t = \alpha_0 + \sum_{k=1}^p \alpha_k Y_{t-k} + \sum_{k=1}^p \beta_k X_{t-k} + u_{it} \quad (3)$$

where p is a suitably chosen positive integer: α_k and β_k , $k=0,1,2,3,\dots,p$, are constants; and u_1 and v_1 are the usual disturbance terms with zero mean and finite variance. The null hypothesis that X_t does not Granger-cause Y_t is rejected if β_k , $k > 0$ in the first equation is jointly significantly different from zero according to a standard joint test (e.g., an F test). Similarly, Y_t Granger causes X_t if the coefficients of ϕ_k and $k > 0$ in the second equation are jointly different from zero. A bidirectional causality (or feedback) relation exists if both β_k and ϕ_k , $k > 0$, are jointly different from zero.

3 RESULTS AND DISCUSSION

3.1 Unit root tests

In analyses of time series data, it is important that the study variables are stationary, which means that the means and variances of the variable data are the same. Accordingly, Levin-Lin-Chu unit root tests were performed to test the stationarity of the study variables, viz., the number of COVID-19-infected patients (NCASE) and of deaths (DEATH) due to COVID-19. The results are reported in Tables 1 and 2.

The test results presented in Tables 1 and 2 reveal the two variables under study, NCASE and DEATH, to be stationary in level since the Levin, Lin and Chu t-statistics are found to be highly significant ($p < 0.0000$). Hence, the variables under study are stationary.

Table 1: Unit root test results for the variable NCASE.

Method	Statistic	Prob**
Levin, Lin & Chu t*	-52.6381	0.0000

** Probabilities are computed assuming asymptotic normality.

Table 2: Unit root test results for the variable DEATH.

Method	Statistic	Prob ^{**}
Levin, Lin & Chu t*	-52.6381	0.0000

**Probabilities are computed assuming asymptotic normality.

3.2 Summary statistics

The highest numbers of new COVID-19 infections were registered in August 2020 (181817). The lowest numbers of new COVID-19 infections were registered in February 2021. Overall, during the study period 786990 (3rd July 2020 to 31st March 2021), COVID-19 infections were registered across Tamil Nadu (Table 3).

Table 3: Summary statistics of new COVID-19 cases.

MONTH	Obs.	Sum.	Std. Dev.	Skew.	Kurt.
Jul-2020	37	146815	6161.377	4.438891	24.44422
Aug-2020	37	181817	5959.207	3.832259	19.95260
Sept-2020	37	169438	5437.915	3.628216	17.49640
Oct-2020	37	126892	5412.053	4.424521	23.90251
Nov-2020	37	57375	2635.568	4.450735	24.05863
Dec-2020	37	36068	1695.882	4.458505	24.06697
Jan-2021	37	20304	965.4821	4.471459	24.11384
Feb-2021	37	13187	713.3955	4.597593	25.06835
Mar-2021	37	35094	2241.262	4.896154	27.48709
Total	333	786990	4373.680	5.130628	35.95995

The highest number of deaths due to COVID-19 occurred in August 2020 (3387), and the lowest number (140) of deaths occurred in February 2020. In total, during the study period, 11022 deaths were registered due to COVID-19 in Tamil Nadu (Table 4).

Table 4: Summary statistics of the number of deaths due to COVID-19 infection.

MONTH	Obs.	Sum.	Std. Dev.	Skew.	Kurt.
Jul-2020	37	2172	120.4168	4.779336	26.67768
Aug-2020	37	3387	109.8220	3.984666	21.12717
Sept-2020	37	2266	83.24108	3.982086	20.84636
Oct-2020	37	1601	73.28659	4.490933	24.60549
Nov-2020	37	589	34.13973	4.733719	26.36777
Dec-2020	37	410	26.70973	5.001539	28.38716
Jan-2021	37	234	16.14871	5.010479	28.43755
Feb-2021	37	140	8.531429	4.789554	26.83465
Mar-2021	37	223	15.65511	4.523911	24.03041
Total	333	11022	73.33554	5.989940	48.45967

3.3 Panel Cointegration Test

To estimate the cointegration relationship between DEATH due to COVID-19 and the number of COVID-19

cases, the Pedroni Cointegration Test (with no deterministic trend, with deterministic intercept and trend; and with no deterministic intercept or trend) was performed in addition to the Kao Cointegration Test [17]. The test results are presented in Tables 5 through 8.

The results of the Pedroni tests are presented in Tables 5 through 8. The test results reveal that in eleven tests the null hypothesis of no cointegration is rejected since most of the test statistics p values are < 0.0.000, indicating that cointegration exists; i.e., there is a long-term relationship between the number of deaths due to COVID-19 and the number of COVID-19 infection cases.

Table 5: Characteristics of Pedroni Cointegration Test (No deterministic trend).

Name of Test Statistic	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	1.971871	0.0243	-1.794892	0.9637
Panel rho-Statistic	-2.551858	0.0054	-3.980807	0.0000
Panel PP-Statistic	-13.44748	0.0000	-19.80770	0.0000
Panel ADF-Statistic	-15.96736	0.0000	-16.59308	0.0000
Group rho-Statistic	-1.212523	0.1127		
Group PP-Statistic	-27.62273	0.0000		
Group ADF-Statistic	-24.37444	0.0000		

Table 6: Characteristics of Pedroni Cointegration Test (Deterministic Intercept and Trend).

Name of Test Statistic	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	Statistic	Prob.	Weighted Statistic	Prob.
Panel rho-Statistic	-1.458627	0.9277	-6.488375	1.0000
Panel PP-Statistic	-0.223232	0.4117	-0.066714	0.4734
Panel ADF-Statistic	-17.39999	0.0000	-20.62444	0.0000
Group rho-Statistic	-16.54775	0.0000	-16.09085	0.0000
Group PP-Statistic	2.665503	0.9962		
Group ADF-Statistic	-24.76215	0.0000		

Table 7: Characteristics of Pedroni Cointegration Test (No Deterministic Intercept or Trend).

Name of Test Statistic	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	7.577666	0.0000	2.005212	0.0225
Panel rho-Statistic	-7.125280	0.0000	-8.839066	0.0000
Panel PP-Statistic	-10.70637	0.0000	-13.47197	0.0000
Panel ADF-Statistic	-12.84638	0.0000	-13.42705	0.0000
Group rho-Statistic	-4.318797	0.0000		
Group PP-Statistic	-21.62959	0.0000		
Group ADF-Statistic	-21.31247	0.0000		

Table 8: Characteristics of the Kao Cointegration Test (No Deterministic Trend).

Test Name	t-Statistic	Prob.
ADF	-15.21832	0.0000

In the long run, both of the two study variables can move together. They have a long-run relationship. When the variables are cointegrated, it is valid to run a long-run model, such as the Panel FMOLS model (long-run model).

3.4 Panel Fully Modified Least Squares

To study the long-run equilibrium relationship between COVID-19 infection- cases and the number of deaths due to such infection, the FMOLS method is employed with the number of deaths due to COVID-19 as the dependent variable and the number of newly infected COVID-19 patients as the independent variable. The results are presented in Table 9.

Table 9: Characteristics of the panel fully modified least squares test.

Name of Variable	Coefficient	Std. Error	t-Statistic	Prob.
NCASE	0.016510	0.000321	51.44165	0.0000
R-squared	0.894811	Mean dependent var.		29.89865
Adjusted R-squared	0.879726	S.D. dependent var.		64.73505
S.E. of regression	22.45047	Sum squared resid.		130038.1

The estimated long-run model is as follows:
 $DEATH = 0.0165104117428 * NCASE + EQN_01EFACT$
 $(R^2 = 92\%)$

From Table 9, the long-term coefficient (0.016510) is positive and highly significant ($p < 0.0000$), indicating that if there is a one per cent increase in NCASE, the number of deaths due to COVID-19 is increased 1.6%.

Table 10 depict the coefficient of confidence intervals (CI). As shown in the following table and the Fig.1. the estimated long-run coefficient (0.016510) lies in the 99% CI.

Table 10: Coefficient Confidence Interval

Variable	Coefficient	90% CI		95% CI		99% CI	
		Low	High	Low	High	Low	High
NCASE	0.017	0.016	0.017	0.016	0.017	0.016	0.017

Table 11: Characteristics of the estimated trend coefficients for each district (cross-section)

Sr. No.	District Name	Intercept	Slope
1	Ariyalur	-0.6747	0.0122
2	Chengalpattu	-5.0610	0.0142
3	Chennai	-69.6899	0.0187
4	Coimbatore	-3.6511	0.0124
5	Cuddalore	-0.3452	0.0115
6	Dharmapuri	0.4786	0.0089
7	Dindigul	-5.3143	0.0219
8	Erode	-5.3642	0.0122
9	Kallakurichi	-1.0707	0.0129
10	Kancheepuram	-5.2306	0.0156
11	Kanyakumari	-10.2036	0.0239
12	Karur	-0.3696	0.0091
13	Krishnagiri	-2.9314	0.0161
14	Madurai	-15.2189	0.0298
15	Nagapattinam	-1.5755	0.0176
16	Namakkal	0.3669	0.0090
17	Nilgiris	0.1996	0.0063
18	Perambalur	-0.5862	0.0134
19	Pudukottai	-2.0367	0.0165
20	Ramanathapuram	-1.6468	0.0269
21	Ranipet	-1.6204	0.0140
22	Salem	-9.8262	0.0173
23	Sivagangai	-8.1197	0.0327
24	Tenkasi	-1.9733	0.0230
25	Thanjavur	-2.9443	0.0158
26	Theni	0.8517	0.0109
27	Thirupathur	-1.1407	0.0187
28	Thiruvallur	-9.2406	0.0164
29	Thiruvannamalai	-2.0024	0.0184
30	Thiruvarur	-8.6868	0.0237
31	Thoothukudi	-2.8544	0.0114
32	Tirunelveli	-9.2313	0.0234
33	Tiruppur	-4.7373	0.0138
34	Trichy	-5.9312	0.0166
35	Vellore	-6.1750	0.0214
36	Villupuram	-0.6197	0.0077
37	Virudhunagar	-4.0454	0.0165

The estimated trend coefficients of each district were estimated and are presented in Table 11 for the study period. A suitable interpretation could be made as above for each district.

3.5 Causality test

To assess whether causal relationships exist among the variables and to determine the direction of the causality, the Granger test of causality was employed. The results are presented in Table 12. The test results reveal that the null hypothesis of no causality between the independent and dependent variables running in either direction is rejected. Hence, bidirectional causality exists between the study variables.

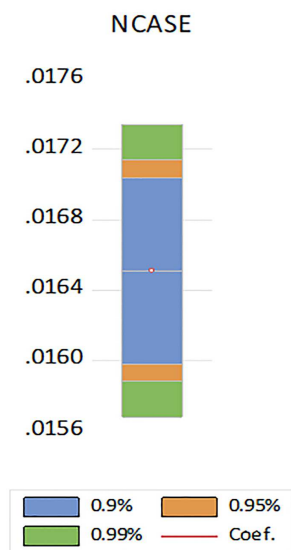


Fig. 1: Estimated Coefficient Confidence Intervals

Table 12: Pairwise Granger Causality Test.

Null - Hypothesis:	Obs.	F-Statistic	Prob.
NCASE does not Granger Cause DEATH	259	9.42128	0.0001
DEATH does not Granger Cause NCASE		29.7538	2.E-12

4 CONCLUSION

During the study period (3rd July 2020 to 31st March 2021), the highest number of infections, 181817, and the highest number of deaths, 3387, were registered in August 2020. The lowest number of new COVID-19 infection cases (13187.00) and the lowest number of deaths (140) were registered in February 2021. Overall, during the study period, 78,6,990 infected cases and 11,022 deaths were registered in Tamil Nadu. The FOMS was found suitable to study the long-run equilibrium relationships between the number of COVID-19 infection cases and deaths due to COVID-19 infections. The long-term coefficient (0.016510) was positive and highly significant, indicating that if there was a one per cent increase in NCASE, the number of deaths due to COVID-19 would increase by 1.6%. Bidirectional causality exists between the number of COVID-19 infection cases and the number of deaths due to COVID-19.

Acknowledgement

Authors are highly thankful to Dr.K.Senthamarai Kannan, Senior Professor and Head, Department of Statistics,

Manonmaniam Sundaranar University, Tirunelveli – 627 012, Tamil Nadu State, India, for helpful discussion and encouragement while preparing this paper

Conflict of Interest

The authors declare that they have no conflict of interest

References

- [1] C. Anastassopoulou, L. Russo, A. Tsakris, C. Siettos, Data-based analysis, modelling and forecasting of the COVID-19 outbreak, *PLoS ONE*, **15**(3): e0230405 (2021).
- [2] P.K. Narayan, R. Smyth and A. Prasad, Electricity consumption in G7 countries: A panel cointegration analysis of residential demand elasticities, *Energy Policy*, **35**(9), 4485-4494 (2007).
- [3] P. Sadorsky, Trade and energy consumption in the Middle East, *Energy Economics*, **33**(5), 739-749 (2011).
- [4] S. Farhani and J.B. Rejeb, Energy consumption, economic growth and CO2 emissions: evidence from Panel Data for MENA region, *International Journal of Energy Economics and Policy*, **2**(2), 71-81 (2012).
- [5] E. Alaa, Electricity demand analysis and forecasting: A panel cointegration approach, *Energy Economics*, **40**(C), 251-258 (2013).
- [6] A. Rajarathinam and P. Tamilselvan, Autoregressive Distributed Lag Model of COVID-19 cases and deaths, *Journal of Statistics Applications & Probability*, **10**(3), 767-777 (2021).
- [7] A. Rajarathinam and P. Tamilselvan, Vector error correction modeling of covid-19 infected cases and deaths, *Journal of Statistics Applications & Probability*, **11**(1), 205-214 (2022).
- [8] B. Baltagi, *Econometric Analysis of Panel Data*, New York: John Wiley & Sons, (2008).
- [9] C. Hsiao, *Analysis of Panel Data*, 2nd edition. Cambridge University Press, Cambridge, MA, (2003).
- [10] D.N. Gujarati, D.C. Porter, G. Sangeetha, *Basic Econometrics*, 5th edition. McGraw Hill Education, New York, NY, (2017).
- [11] A. Levin, C.F. Lin, C.S.J. Chu, Unit root tests in panel data: asymptotic and finite-sample properties, *Journal of Econometrics*, **108**, 1-24 (2002).
- [12] K. Hadri, Testing for stationarity in heterogeneous panel data, *The Econometrics Journal*, **3**, 148-161 (2000).
- [13] P. Pedroni, Panel co-integration: asymptotic and finite sample properties of pooled time series tests with an application to PPP hypothesis: new results. *Econometric Theory*, **20**, 597-627 (2004).
- [14] M.S. Karimi and H. Karamelikli, Electricity Demand in MENA Countries : A Panel Cointegration Analysis, *Iranian Economic Review*, **20**(1), 81-92 (2016).
- [15] P.C. Phillips and B.E. Hansen, Statistical inference in instrumental variables regressions with I(1) processes, *Review of Economic Studies*, **57**, 99-125 (1990).
- [16] C.W.J. Granger, Investigating causal relations by econometric models and cross-spectral methods, *Econometrica*, **37**, 424-438 (1969).

- [17] C. Kao and M.H. Chiang, On the estimation and inference of a cointegrated regression in panel data. In Nonstationary Panels, Panel Cointegration, and Dynamic Panels, *Advances in Econometrics*, **15**, 179–222 (2000).



A. Rajarathinam

is a Professor of Statistics in the Department of Statistics at Manonmaniam Sundaranar University, Tirunelveli, India. He received his, M.Sc. and M.Phil. degrees in Statistics from Annamalai University, Chidambaram, and a PGDCA degree from Bharathidasan

University, Trichirapalli, Tamil Nadu State, India. He was also conferred with a Ph.D. degree in Agricultural Statistics by the Gujarat Agricultural University, Gujarat State, India. He previously taught at Anand Agricultural University, Anand, Gujarat State, India in the capacity of an Associate Professor. His research interests include Applied Statistics, Multivariate Analysis, Econometrics modeling and Design of Experiments. He has published more than 30 research papers in reputed international scientific journals. So far, he has guided 10 Ph.D. scholars and published 3 books. He has visited several foreign countries to attend International Conferences and present papers. Furthermore, he is an editor for the International Journal of Agricultural and Statistical Sciences.



J. B. Anju is a Research Scholar in the Department of Statistics at Manonmaniam Sundaranar University, Tirunelveli, India. She received her B.Sc Mathematics ,M.Sc Statistics degrees from university of Kerala, India and DCA from C-DIT, under Government of

Kerala ,India. She has participated and presented papers in 3 international conferences . Her Research interests are Econometrics Modeling and Applied Statistics and her current research topic is Modeling and Monitoring COVID-19 Monthly Infected Cases and Deaths.