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Interdepencies Between Aviation Demand and Economic Growth in India:Cointegration Equation Estimation

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Abstract

The main purpose of the paper is to empirically examine the aviation-led growth hypothesis for India by testing causality between aviation and economic growth. We resort to econometric tests such as unit root tests and test of cointegration purposed by Johansen (1988). Fully Modified OLS, Dynamic OLS and Conical Cointegration Regression are used to estimate the cointegration equation for time span of 1970 to 2012. Empirical results reveal the existence of relationship between aviation demand and economic growth. Graphic methods such as Cholesky Impulse Response function (both accumulated and non-accumulated) and variance decomposition have also been applied to render the analysis rigorous. The positive contribution of aviation demand to economic growth is similar in all three estimation techniques of cointegration equation. Findings help in lime-lighting the importance of aviation industry in economic growth for a developing country like India.

Keywords: Air Transportation, Economic Growth, Cointegration, Unit Root Tests, Fully Modified Ordinary Least Square (FMOLS), Dynamic Ordinary Least Square (DOLS), Conical Cointegraton Regression (CCR), Aviation Multiplier.

Introduction

Ever since wheel was invented, transportation has been playing its role in transporting human beings (services) and goods. Dependence of economic activities, both from production (supply) and consumption (demand) side on transportation has been ever increasing. This paper analyses one type of transportation 'aviation/air transportation' as variable in association with economic growth. Recent work on this issue has shown positive effects of aviation on economic growth of a country. Nearly no attention has been paid to the empirical analysis of the relationship between economic growth and aviation of India. This creates the justification of this research. Focus of this research is to explore the causal relationship between aviation and economic growth in India. To measure aviation, we used 'passenger carried' (PC). While for incorporating economic growth, GDP in constant local currency unit is used. For statistical analysis, this paper resorts to econometric tests such as unit root tests (ADF, Phillips Perron) and test of cointegration purposed by Johansen (1988). The time span covered by the study is 1970 to 2012. This paper scrutinizes the relationship between aviation and economic growth by applying the Johansen cointegration approach for the long-run and the standard error correction method (ECM) for the short-run. This paper contributes to the existing methodology in Marazzo *et al*., (2010) by using FMOLS, DOLS and CCR to estimate cointegrating equations. For a recent application of FMOLS, see Mehmood, *et al.*, (2012).

Literature review

The literature on aviation especially in India is quite limited. A few studies that exist are as follows: Mukherjee and Sachdeva (2003), have observed to and fro of the privatization program of transport sector during 1990s. They overviewed two subsectors; air transport and maritime and assessed the till date progress. It has become a common consensus that efficiency in the transport sector has major spillover effects on the competitiveness of both goods and services. Accordingly, this paper suggests that government should facilitate them to make their decisions on their own this will enhance their efficiency in both the public and private sectors.

Mathur (2004), analyzed the technical efficiency of Delhi Airport by using monthly data of international and total traffic of aircrafts, passengers & cargo movements from March 2000 to July 2004. He compared it with other domestic airports as well. For efficiency measurement Data Envelopment Analysis (DEA) has been used and has shown the significant results. The costs and benefits of privatization of the Delhi Airport with other airports were also compared. The innovative research, however, on aviation-growth nexus was conducted by Marazzo *et al.,* (2010). They empirically tested the relationship between aviation demand and GDP for Brazil. They used passenger-kilometer as a proxy of aviation demand and found a long-run equilibrium between the two variables using bi-variate Vector Autoregressive Model. Their findings reveal strong positive causality from GDP to aviation demand but relatively weaker causality other way around. Robustness tests were applied through Hodrick and Prescott filter to capture the cyclical components of the series and the results withstood these robustness tests. Their interpretation of the positive causality indicates the existence of multiplier effect.

Oxford Economic Forecasting (2011) discussed the role of different channels through which aviation sector in India generates economic welfares for its customers and international economy. The report has focused on the basic economic tools of the industry i.e., National income, employment generation that is supported by the industry. The well-being of travelling citizens has also been predictably quantified in this study. Approximately 76% customers of airlines that serve Indian airports are Indian residents. Similarly, 45% shippers using air freight services are Indian companies. Indian-based airlines were responsible for carrying 71% of passengers and 78% of freight. Thus it has supported 0.5% of Indian GDP and 1,723,000 jobs or 0.4% of the Indian labor force. By including the participation of tourism, it has increased to 1.5% of Indian GDP and 8.8 million jobs, or 1.8% of the labor force. Thus, salaries, profits and tax revenues have generated multiplier effects on Indian national income. Mehmood and Kiani (2013) examine the aviation-led growth hypothesis for Pakistan by testing causality between aviation and economic growth using unit root tests and cointegration tests. Using the data from 1973 to 2012, they innovated the work of Marazzo *et al.*, (2010) by used Fully Modified OLS and Dynamic OLS for the estimation of cointegration equation. Estimations reveal that positive contribution of aviation demand to economy is more prominent as compared to that of economic growth to aviation demand. They found positive contribution of aviation demand to economic growth is similar in both FMOLS and DOLS. A study that links aviation demand and economic growth of India is an unaddressed topic in empirical literature. We intend to fill this gap by fulfilling the following objective. The objective of the paper is mentioned here. The paper aims at analyzing the aviation-growth nexus in India. Specific proposition is as follows:

P_A: *There exists a positive relationship between Aviation Demand and Economic Growth in India.*

For scrutinizing this proposition, data and methodology are explained as follows:

Data and Methodology

The demand for aviation is proxied by passengers carried via air transport following (Marazzo, Scherre & Fernandes, 2010) and economic growth by GDP is used in local currency (in constant terms). Data of concerned variables is taken from World Development Indicators (WDI). For India, data on passengers carried is available from 1970 to 2012, allowing us to use 43 observations for time series analysis. EViews Standard Version 7.2 is used for all estimations. Before conducting the inferential analysis, line chart and descriptive analysis is conducted.

Descriptive Statistics

Economic growth is proxied by GDP (Current LCU), while demand for aviation is proxied by 'passengers carried by air transport' (PC). The line charts of GDP (Current LCU) and passengers carried are plotted against time in years. Both of these shows trend and intercepts. This information will be helpful in conducting the stationarity tests.

Table 1: Descriptive statistics of GDP and PC

Statistic	Passengers Carried by Air Transport	GDP
Mean	18177047.73	381420762676.95
Median	11785200.00	279412727492.30
Maximum	73173381.21	1046657808545.31
Minimum	2554000.00	119767317250.61
Std. Dev.	17774237.57	267960800653.19
Observations	43	43

Line Charts

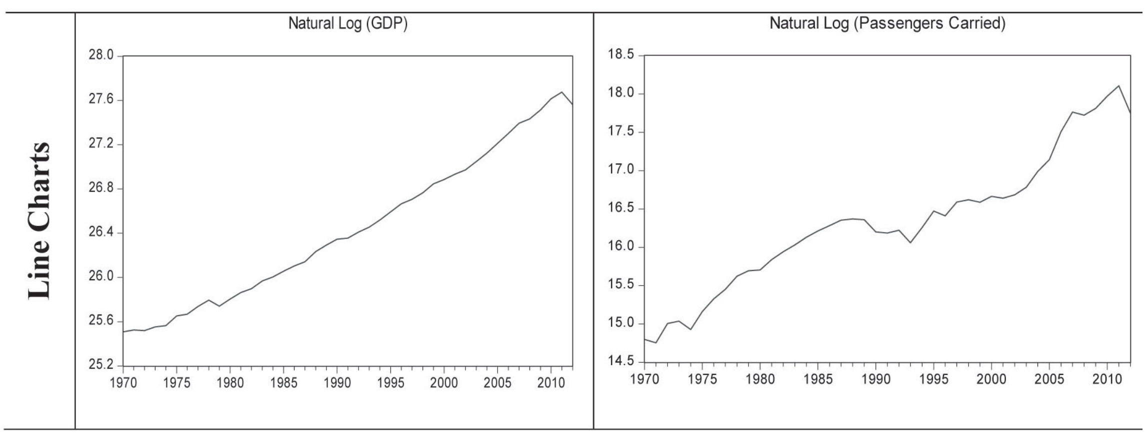

Fig. 1: Line Charts of LGDP and LPC

Note: Line charts of GDP and PC are plotted to reveal intercept and trend of the variables.

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Inferential Analysis

Stationarity Tests

Both stationarity tests, Augmented Dickey Fuller (ADF) and Phillip Peron (PP), are applied with the assumptions that GDP and PC in their logarithmic form reveal intercept and trend. Both variables are stationary at first level using ADF and PP tests. So LGDP and LPC variables are stationary at I(1). Such is tabulated in table 2.

5.2. Augmented Dickey Fuller Test

For scrutinizing non-stationarity in a time series Augmented Dickey–Fuller test (ADF) test was purposed by Dickey and Fuller (1979). In order to check if the series carry one unit root, the ADF test presents the following speciûcation:

$$\Delta Y_t = \alpha + \beta T + \varphi Y_{t-1} + \sum_{i=1}^{p} \Delta Y_{t-i} + \varepsilon_t \qquad (1)$$

where Y_t and ΔY_t are respectively the level and the ûrst difference of the series, T is the time trend variable, and α, β, φ, Ψ are parameters to be estimated. The p lagged difference terms are added in order to remove serial correlation in the residuals.

The null hypothesis is H_0: $\varphi \neq 0$ and the alternative hypothesis is H_1: $\varphi \neq 0$. ε_t is the error term presenting zero mean and constant variance. First order integrated series can present stationary linear combinations (I(0)). In these cases, we say variables are cointegrated. It means there is a long-run equilibrium linking the series, generating a kind of coordinated movement over time. In order to assess the existence of cointegration between I(1) series, Engle and Granger (1987) proposed a regression between two non-stationary variables (Y_t, X_t) to check the error term integration order. If the error term is stationary one can assume the existence of cointegration.[1] Thus:

$$Y_t = \alpha + \beta X_t + \mu_t \qquad (2)$$

is an equation of cointegration if μ_t is stationary. This condition can be evaluated through the ADF test. A more recent approach is provided by Johansen and Juselius (1990). They suggested an alternative method which has been applied under the following speciûcation:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + \beta X_t + \varepsilon_t \qquad (3)$$

Where $\sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$, Yt is a vector of k non-stationary (I(1)) variables, X_t is a vector of d deterministic variables and ε_t is a vector of random terms (zero mean and ûnite variance). The number of cointegration relations is represented by the rank of P coefûcient matrix. The Johansen method relies on estimating the P matrix in an unrestricted form and testing whether it is possible to reject the imposed restrictions when reducing the rank of P. The maximum likelihood test, which checks the hypothesis of a maximum number of r cointegration vectors, is called the trace test. It should be highlighted that variables under cointegration analysis should present the same integration order. If one concludes that cointegration exists in (3), then there is at least one stationary variable that may be included in the model. This representation is known as Error Correction Model (ECM), speciûed as follows:

[1]For more see Bouzid (2012).

$$\Delta Y_t = \lambda + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{n} \beta_j \Delta X_{t-j} + \phi Z_{t-1} + \varepsilon_t \quad (4)$$

Where ë is the constant term, α, β, φ, are coefûcients, m and n are the required number of lags to make the error term ε_t a white noise and Z_{t-1} is the cointegration vector ($Z_{t-1} = Y_{t-1} - \delta X_{t-1}$), where δ is a parameter to be estimated). In this case, Z_{t-1} works as an error correction term (ECT). The ECT provides valuable information about the short run dynamics between Y and X. In Eq. (4), all the terms are I(0).

Phillip Perron Test

Phillips and Perron (1988) propose an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented DF test equation [$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \epsilon_t$] and modifies the t-ratio of the á coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\bar{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{1/2} - \frac{T(f_0-\gamma_0)(se(\hat{\alpha}))}{2 f_0^{1/2} s} \quad (5)$$

Where $\hat{\alpha}$ is the estimate, and t_α the t-ratio of á, $se(\hat{\alpha})$ is coefficient standard error, and s is the standard error of the test regression. In addition, is a consistent estimate of the error variance in equation (1) (calculated as $(T-k)s^2/T$, where k is the number of regressors). The remaining term, $\mathbf{f_0}$, is an estimator of the residual spectrum at frequency zero.

Table 2: ADF and PP Tests

Test (Constant, Trend)	Level of Stationarity	Variables	t-Statistics	Probability
I	II	III	IV	V
Augmented Dickey Fuller (ADF)	At level	LGDP	-2.7243	0.2326
		LPC	-1.7895	0.6920
	At first difference	ÄLGDP	-4.5539	0.0039
		ÄLPC	-4.9285	0.0014
Phillips & Perron (PP)	At level	LGDP	-2.7196	0.2344
		LPC	-2.0596	0.5525
	At first difference	ÄLGDP	-3.9024	0.0209
		ÄLPC	-5.0170	0.0011

Notes: (i) Constant and Trend option for ADF and PP tests are selected on the basis of line plots of LGDP and LPC. (ii) All the ADF and PP test show stationarity at 1st difference with 1% or 5% level of significance.

Johansen cointegration test is applied on the variables of concern and mathematically this is expressed in equation (6) and (7):

$$\Delta LPC_t = \alpha_1 + \sum_i \alpha_{11}(i) \Delta LPC_{t-i} + \sum_i \alpha_{12}(i) \Delta LGDP_{t-i} + \beta_1 Z_{t-1} + e_{1t} \quad (6)$$

$$\Delta LGDP_t = \alpha_2 + \sum_i \alpha_{21}(i) \Delta LPC_{t-i} + \sum_i \alpha_{22}(i) \Delta LGDP_{t-i} + \beta_2 Z_{t-1} + e_{2t} \quad (7)$$

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Here ÄLPC$_{t-i}$ and ÄLGDP$_{t-i}$ are the lagged differences which seize the short term disturbances; e_{1t} and e_{2t} are the serially uncorrelated error terms and Z_{t-1} is the error correction (EC) term, which is obtained from the cointegration relation identiûed and measures the magnitude of past disequilibrium.

Table 3: Johansen-Juselius Likelihood Cointegration Tests

Null	Alternative	Statistic (LGDP & LPC)	Critical Value (95%)
I	II	III	IV
		Maximal eigenvalue test	
$\gamma = 0$	$\gamma = 1$	16.2264	15.8921
		Trace test	
$\gamma = 0$	$\gamma \geq 1$	24.1072	20.2618

Notes: (i) Values of Maximal eigenvalue test and Trace tests.
(ii) Optimum lag length is '2' in this case which is selected using the SIC and AIC.

Option of 'Intercept & No Trend' give values of Maximal eigenvalue test and Trace tests reveal the existence of one cointegrating vector. Cointegration is evidenced, using which estimation of cointegrating equations is conducted in the next step.

Vector Error Correction Model

The model is a ûrst order VEC (Vector Error Correction) model as shown in equation (6) & (7). The lag length was found to be '2' which is established on the basis of SI and AI criteria. Based on column 1 of table 3, the cointegration vector conûrms the expected positive relationship between aviation demand and economic growth (1 LPC = 1.474 LGDP). More specifically, an increase of 1 % in PC leads to 1.474 % increase in GDP.

Impulse Response Function

The intensity of responsiveness to shocks among variables is assessed through impulse-response function (IRF) analysis.[2] Shocks are deûned as one standard deviation in the innovations. The effect is also transmitted to other endogenous variables through the VECM dynamic structure. IRF tracks the effect of shocks on each innovation over all endogenous variables in the system. If innovations are simultaneously uncorrelated, IRF can be directly interpreted. The i^{th} innovation ε_t is just a shock on the i^{th} endogenous variable Y_t. Since, innovations are usually correlated, Cholesky decomposition is applied for making inference about IRF. This tool makes the innovations become orthogonal (uncorrelated).

Figure 2 (panel 2(a) and 2(b)) give IRF plot for a 10-period-horizon in a year by year fashion. Response of LPC is positive and strong to a shock in LGDP. Maximum impact takes place after two years (t + 2) as seen in Figure 2. While LGDP shows no response till the end of second year and gradually falls negative onwards. This finding conform to intuitive outcome in Marazzo et al. (2010) that refers a strong response of GDP to shock in aviation demand as 'aviation multiplier effect'. It is justified since the economy is effected by an abrupt increase in air transport demand in a slower and more moderated way. While on other hand, aviation demand reacts readily and significantly to a shock on economic growth. In panel 2(c) and 2(d), the responses over time are amassed to analyze the long-run effects of the shocks. On completion of ten periods, aviation demand has increase by 76%. While a shock on LPC does not increase LGDP rather affects it negatively by 2.0% after ten periods.

[2]The condition of ceteris paribus holds.

Forecasting Error Variance Decomposition (FEVD)

It provides the proportion of a series forecasting error variance due to shocks on itself and shocks on other variables in a system. Panel 2(e) and 2(f) depict that approximately 65% of LPC forecasting error variance can be attributed to LGDP, while no LGDP forecasting error variance can be assigned to LPC. Major part of LPC forecasting error variance explained by LGDP is in lines with IRF analysis explained above. It also depicts that in forecasting LPC, LGDP plays an important role. Yuan et al. (2007) terms FEVD as an out-of-sample causality test.

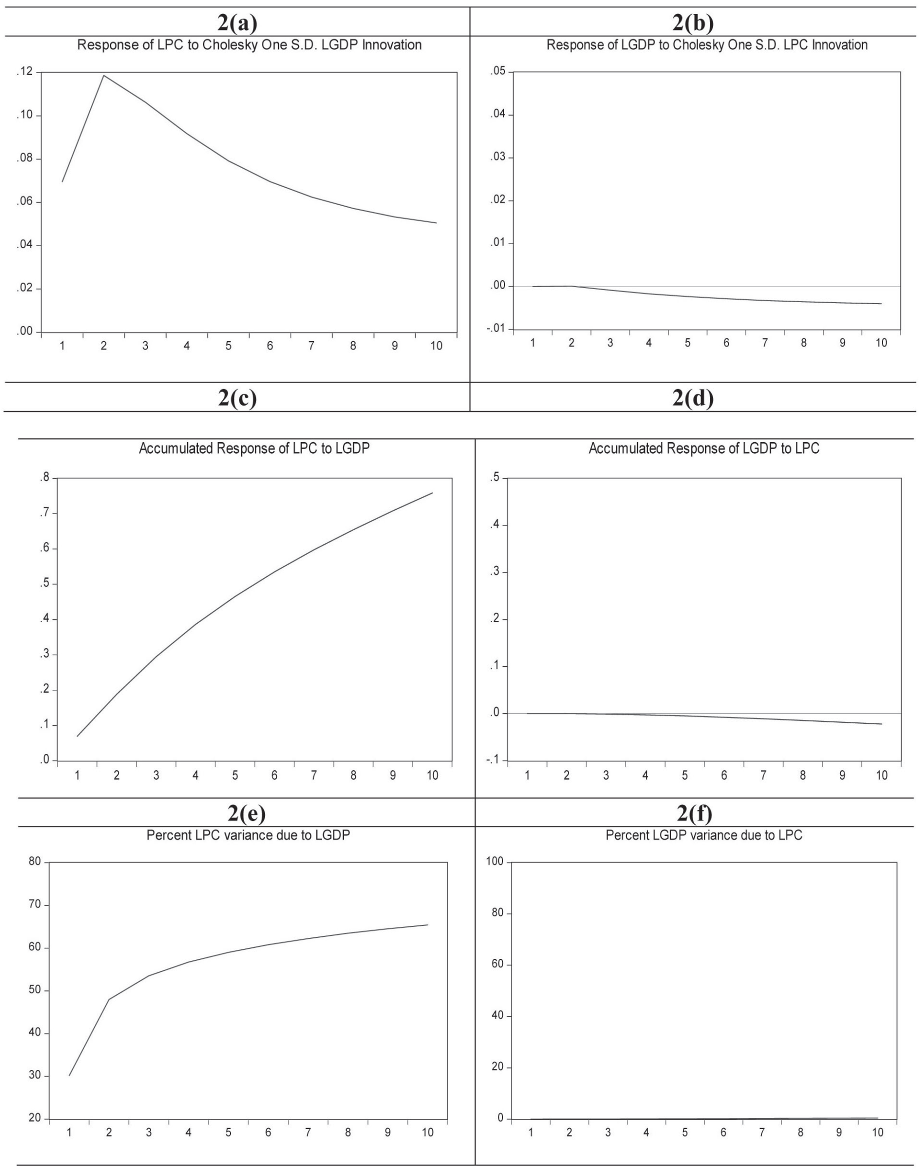

Fig. 2: Matrix for ECM, Impulse Response Function and Variance Decomposition

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Cointegrating equation is estimated using recently developed econometric methodologies, namely: fully modified ordinary least squares (FMOLS) of Phillips and Hansen (1990), dynamic ordinary least squares (DOLS) technique of Stock and Watson (1993) and Conical Cointegration Regression (CCR) of Park (1992). These methodologies provide a check for the robustness of results and have the ability to produce reliable estimates in small sample sizes.

Fully Modified Ordinary Least Squares (FMOLS)

On the basis of VAR model results, cointegrating regression is estimated. In a situation, where the series are cointegrated at first difference 'I(1)', Fully modified ordinary least squares (FMOLS) is suitable for estimation. FMOLS is attributed to Phillips and Hansen (1990) to provide optimal estimates of cointegrating regressions. FMOLS modifies least squares to explicate serial correlation effects and for the endogeneity in the regressors that arise from the existence of a cointegrating relationship.[3]

$$\mathbf{X_t} = \hat{\Gamma}_{21}' \mathbf{D_{1t}} + \hat{\Gamma}_{21}' \mathbf{D_{1t}} + \hat{\epsilon}_t \quad (8)$$

or directly from the difference regressions

$$\Delta \mathbf{X_t} = \hat{\Gamma}_{21}' \Delta \mathbf{D_{1t}} + \hat{\Gamma}_{21}' \Delta \mathbf{D_{1t}} + \hat{\upsilon}_t \quad (9)$$

Let $\hat{\Omega}$ and $\hat{\Lambda}$ be the long-run covariance matrices computed using the residuals $\hat{\upsilon}_t = (\hat{\upsilon}_{1t}, \hat{\upsilon}_{2t}')'$. Then we may define the modified data

$$\mathbf{y}_t^* = \mathbf{y}_t - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{\upsilon}_2 \quad (10)$$

An estimated bias correction term

$$\hat{\lambda}_{12}^* = \hat{\lambda}_{12} - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{\Lambda}_{22} \quad (11)$$

The FMOLS estimator is given by

$$\hat{\theta} = \begin{bmatrix} \hat{\beta} \\ \hat{\gamma}_1 \end{bmatrix} = \left(\sum_{t=1}^{T} Z_t Z_t'\right)^{-1} \left(\sum_{t=1}^{T} Z_t y_t^* - T \begin{bmatrix} \hat{\lambda}_{12}^{*\prime} \\ 0 \end{bmatrix}\right) \quad (12)$$

Where $Z_t = (X_t', D_t')'$. The key to FMOLS estimation is the construction of long-run covariance matrix estimators and . Before describing the options available for computing and , it will be useful to define the scalar estimator

$$\hat{\omega}_{1.2} = \hat{\omega}_{11} - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{\omega}_{21} \quad (13)$$

Which may be interpreted as the estimated long-run variance of conditional on . We may, if desired, apply a degree-of-freedom correction to.

Dynamic Ordinary Least Square (DOLS)

Dynamic Ordinary Least Squares (DOLS) is attributed to Saikkonen (1992) and Stock & Watson (1993). DOLS is a simple approach to constructing an asymptotically efficient estimator that eliminates the feedback in the cointegrating system. Technically speaking, DOLS involves augmenting the cointegrating regression with lags and leads of so that the resulting cointegrating equation error term is orthogonal to the entire history of the stochastic regressor innovations:

$$\mathbf{y_t = X_t'\beta + D_{1t}'\gamma_1 + \sum_{j=-q}^{r} \Delta X_{t+j}'\,\delta + \upsilon_{1t}} \tag{14}$$

Under the assumption that adding **q** lags and **r** leads of the differenced regressors soaks up all of the long-run correlation between υ_{1t} and υ_{2t}, least-squares estimates of (β',γ',)' have the same asymptotic distribution as those obtained from FMOLS and Conical Cointegration Regression (CCR).

An estimator of the asymptotic variance matrix of may be computed by computing the usual OLS coefficient covariance, but replacing the usual estimator for the residual variance of with an estimator of the long-run variance of the residuals. Alternately, you could compute a robust HAC estimator of the coefficient covariance matrix.

Conical Cointegration Regression (CCR)

The CCR estimator is based on a transformation of the variables in the cointegrating regression that removes the second-order bias of the OLS estimator in the general case. The long-run covariance matrix can be written as:

$$\boldsymbol{\Omega} = \lim_{n\to\infty}\frac{1}{n}E\left(\sum_{t=1}^{n}u_t\right)\left(\sum_{t=1}^{n}u_t\right)' = \begin{bmatrix}\Omega_{11} & \Omega_{12}\\ \Omega_{21} & \Omega_{22}\end{bmatrix} \tag{15}$$

The matrix can be represented as the following sum:

$$\boldsymbol{\Omega = \Sigma + \Gamma + \Gamma'} \tag{16}$$

where

$$\boldsymbol{\Sigma} = \lim_{n\to\infty}\frac{1}{n}\sum_{t=1}^{n}E(u_t u_t') \tag{17}$$

$$\boldsymbol{\Gamma} = \lim_{n\to\infty}\frac{1}{n}\sum_{k=1}^{n-1}\sum_{t=k+1}^{n}E(u_t u_{t-k}') \tag{18}$$

$$\boldsymbol{\Lambda} = \Sigma + \Gamma = (\Lambda_1,\Lambda_2) = \begin{bmatrix}\Lambda_{11} & \Lambda_{12}\\ \Lambda_{21} & \Lambda_{22}\end{bmatrix} \tag{19}$$

The transformed series is obtained as:

$$y_{1t}^{*} = y_{1t} - \left(\Sigma^{-1}\Lambda_2\beta + \left(0,\Omega_{12}\Omega_{22}^{-1}\right)'\right)'u_t \tag{20}$$

$$y_{1t}^{*} = y_{1t} - \left(\Sigma^{-1}\Lambda_2\beta + \left(0,\Omega_{12}\Omega_{22}^{-1}\right)'\right)'u_t \tag{21}$$

The canonical cointegration regression takes the following form:

$$y_{1t}^{*} = \beta' y_{2t}^{*} + u_{1t}^{*} \tag{22}$$

where

$$u_{1t}^{*} = u_{1t} - \Omega_{12}\Omega_{22}^{-1}u_{2t} \quad (23)$$

Therefore, in this context the OLS estimator of (22) is asymptotically equivalent to the ML estimator. The reason is that the transformation of the variables eliminates asymptotically the endogeneity caused by the long-run correlation of y_{1t} and y_{2t}. In addition (23) shows how the transformation of the variables eradicates the asymptotic bias due to the possible cross correlation between u_{1t}, and u_{2t}.

Comparison of the Cointegration Regression Estimates

Estimates of the three estimates techniques are summarized in the table 4:

Table 4: Comparison of the Cointegration Regression Estimates

Estimation Technique	Constant	Coefficient	t-Statistic	S.E.	Adj. R^2	Long-Run Variance	Remarks on Relationship
FMOLS	14.0159	0.7609***	12.4088	0.0613	0.9217	0.1139	+ve & significant
DOLS	13.6820	0.7817***	11.6795	0.0669	0.9254	0.1072	+ve & significant
CCR	14.0293	0.7602***	12.6165	0.0603	0.9217	0.1139	+ve & significant

Note: All the constants and coefficient estimates are significant at 1%, indicated by ***.

Results of all three estimation techniques (FMOLS, DOLS & CCR) for cointegrating regression show a positive relationship between LGDP and LPC. However, DOLS has increases explanatory power of LPC and overall adjusted R^2, as compared to FMOLS and CCR techniques. DOLS has decreased the value to long run variance by a small fraction. Our major concern, however, is to find the nature of relationship between LGDP and LPC, that is found to be positive and significant using all three cointegration equation estimation techniques.

Conclusion

This paper investigated the cointegration, reaction to shocks and relationships between demand for aviation and economic growth in India. The results of this paper imply that aviation and economic growth are cointegrated in the long run and the relationship holds in the short run as well. LPC does not react positively and strongly to a shock in LGDP. While LGDP has an evident positive and strong impact due to shock in LPC. The maximum impact occurs after two years (t + 2) while LGDP shows a negligible reaction in the ûrst period and negative effect in coming years. This can be translated into an aviation multiplier effect. Our innovation into the empirical analysis of estimation of cointegrating vector using FMOLS, DOLS and CCR, corroborate the findings in Marazzo *et al., (*2010).

The positive relationship can be attributed to direct and indirect effects of aviation. Direct effects include transportation of labour force (implicitly of services) and goods. Indirect benefits include benefits that accrue to other industries through backward and forward linkages of aviation industry. This gives further impetus to economic activity and hence growth. In the case of India, aviation industry should get policy attention to play its further ameliorated role in determining economic growth. Formal incentives should be given to aviation industry to upsurge its impact on overall economy of India.

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Footnotes

[1]For more see Bouzid (2012).

[2]The condition of ceteris paribus holds.

[3]See Phillips and Hansen (1990), Hansen (1995) and Saher (2011) for details.

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