WHAT CAUSES WHAT? AVIATION DEMAND AND ECONOMIC GROWTH IN ROMANIA: COINTEGRATION ESTIMATION AND CAUSALITY ANALYSIS

Bilal Mehmood[1]
Acleo Feliceo[2]
Amna Shahid[3]

Abstract:

This paper is empirically analyses the aviation-led growth hypothesis for Romania 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 cointegration 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. Finally Granger causality test is also applied to find the direction of causal relationship. Findings help in chalking out the importance of aviation industry in economic growth for Romania.

Keywords:

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

JEL Classification: L93; O40; C22.

1. Introduction

Role of transportation has been pivotal in transporting human beings (services) and goods since historic times. Economic activities, both from production (supply) and consumption (demand) side depend on transportation. This paper analyses 'aviation/air transportation' as covariate in association with economic growth. Recent work on this issue has shown positive effects of aviation on economic growth of a

[1] Department of Economics, Government College University, Lahore, Pakistan digital.economist@gmail.com
[2] Economic Informatics Department, ASE Bucharest, Romania, felician.alecu@ie.ase.ro
[3] Department of Economics, Government College University, Lahore, Pakistan, samna10@hotmail.com

country. Nearly no heed has been paid to the empirical analysis of the relationship between economic growth and aviation of Romania. This creates the justification of this research. Focus of this research is to explore the causal relationship between aviation and economic growth in Romania. To measure aviation, we used 'passengers carried by air transport' (PAX). 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 and 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) and borrows from Mehmood & Kiani (2013) by using FMOLS, DOLS and CCR to estimate cointegrating equations. Estimation of cointegration equations is becoming a popular practice. For recent application of FMOLS, see Mehmood, et al., (2012).

2. Literature review

Empirical work on aviation-led economic growth is still in its infancy. Oxford Economics (2011), enumerated different channels via which aviation sector of Romania generates economic benefits and supports macroeconomic growth. Analysis of basic macroeconomic indicators show that aviation sector contributes 0.7% of Romanian GDP and 54,000 jobs (0.6%) of the Romanian labor force. Including tourism sector contribution, GDP augments to 0.9% and job creation increases to 78,000 jobs (or 0.9% of the labor force). Approximately, 50% customers of Romanian airlines are Romanian residents. They carry almost 50% of passengers and freight. All such statistical findings reveal that such income and revenue generation creates multiplier effect to the Romanian economy.

To our knowledge no further instances of research on Romanian aviation exist.

While modern research on aviation in relation to economy includes David and Scott (2005) that state aviation has a significant impact on world trade as explorers have discovered trade routes and the technology of transport have improved. The pioneering research on aviation-growth nexus is 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. Mehmood & Kiani (2013) empirically 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 similar positive contribution of aviation demand to economic growth is similar in both FMOLS and DOLS. To do this much-needed research for Romania aviation, this paper aims at analyzing the aviation-growth nexus for Romania. Specific testable proposition is as follows:

P_A: *There exists a causal relationship between Aviation Demand and Economic Growth in Romania.*

For scrutinizing this proposition, data dimensions and sources are explained. Moreover, the econometric methodology is explained as follows:

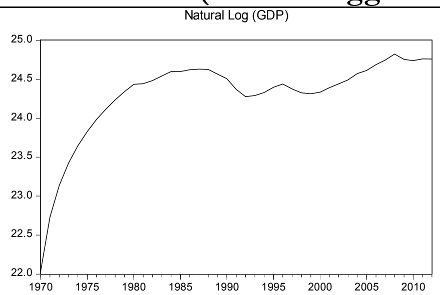
3. Data and Methodology

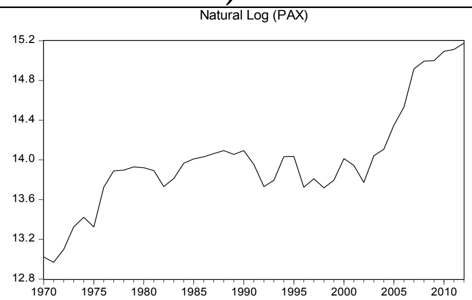
Borrowing from Marazzo et al., (2010) and Mehmood & Kiani (2013), the demand for aviation is represented by 'air transport, passengers carried' and economic growth by GDP is used in local currency (in constant terms). Data for these variables is taken from World Development Indicators (WDI). For Romania data on passengers carried and GDP is available from 1970 to 2012. The time span allows us to use 43 observations for our time series analysis. EViews Standard Version 7.2 is used for all estimations. Before conducting the inferential analysis, line chart is furnished.

4. Description of Variables

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

Figure 1. Line Chart of LGDP and LPAX
(Natural logged forms for GDP and PAX)





Note: Line charts of LGDP and LPAX are plotted that show an intercept (constant) and trend (slope).

5. Inferential Analysis

5.1. Stationarity Tests

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

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 specification:

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

where Y_t and ΔY_t are respectively the level and the first 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.[4] Thus:

$$Y_t = \alpha + \beta X_t + \mu_t \quad \textbf{(2)}$$

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 specification:

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

Where $\sum_{j=1}^{p} A_j - I, \Gamma_j = -\sum_{j=i+1}^{p} A_j$, Y_t 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 finite variance). The number of cointegration relations is represented by the rank of P coefficient matrix. The Johansen method relies on

[4] For more see Bouzid (2012).

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), specified as follows:

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

Where λ is the constant term, α, β, φ are coefficients, 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).

5.3. 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 [$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \varepsilon_t$] and modifies the t-ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

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

Where $\hat{\alpha}$ is the estimate, and t_α the t-ratio of α, $se(\hat{\alpha})$ 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 1. ADF and PP Tests

Using constant and trend	Stationarity	Variables	t-Statistic	Prob. Value
I	**II**	**III**	**IV**	**V**
Augmented Dickey Fuller (ADF)	At level	LGDP	-2.1120	0.5240
		LPAX	-0.4676	0.8874
	At first difference	ΔLGDP	-5.6629	0.0002
		ΔLPAX	-5.6409	0.0000
Phillips & Perron (PP)	At level	LGDP	1.6897	0.9761
		LPAX	-1.3954	0.8479
	At first difference	ΔLGDP	-6.0826	0.0000
		ΔLPAX	-5.5793	0.0002

Notes: (i) t-statistics estimates listed in column IV.

(ii) ADF and PP tests of LGDP & LPAX show stationarity at 1st difference with significance at all levels (1%, 5% & 10%).

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

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

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

Here $\Delta LPAX_{t-i}$ and $\Delta LGDP_{t-i}$ 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 identified and measures the magnitude of past disequilibrium.

Table 2. Johansen-Juselius Likelihood Cointegration Tests

Null	Alternative	Statistic (LGDP & LPAX)	Critical Value (95%)
I	**II**	**III**	**IV**
Maximal eigenvalue test			
$\gamma = 0$	$\gamma = 1$	18.4682	14.2646
Trace test			
$\gamma = 0$	$\gamma \geq 1$	18.6699	15.4947

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.

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.

5.4. Vector Error Correction Model

The model is a first order VEC (Vector Error Correction) model representing short run dynamics and is 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 2, the cointegration vector confirms the expected positive relationship between aviation demand and economic growth.

5.5. Impulse Response Function

The intensity of responsiveness to shocks among variables is assessed through impulse-response function (IRF) analysis.[5] Shocks are defined as one standard deviation in the innovations. The effect is also transmitted to other endogenous

[5] The condition of ceteris paribus holds.

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 yearly and accumulated patterns. Response of LPAX is positive and strong to a shock in LGDP. Maximum impact takes place till sixth year (t + 6) as seen in graph. After 6^{th} year the reponse becomes stable LGDP also shows a sharp response to an innovation in LPAX till 2^{nd} year and them becomes stable. These results are similar to intuitive results in Marazzo et al. (2010) in which authors refers strong response of GDP to shock in aviation demand as 'aviation multiplier effect'. An additional finding is the opposite strong response of aviation demand to shock in GDP. In this case, Romanian economy is affected by an abrupt increase in aviation demand in a strong way. Similarly, aviation demand reacts readily and significantly to a shock on economic growth. In terms of comparison of responsiveness, it is found that:

Response of LPAX to innovation in LGDP > Response of LGDP to innovation in LPAX

In panel 2(c) and 2(d), the responses over time are accumulated to analyze the long-run effects of the shocks. On completion of ten periods, aviation demand has increase by 94.0%. While a shock on LPAX raises the GDP by 22% after ten periods. This comparison of accumulated responses can be put in an inequality as done above:

Accumulated Response of LPAX to LGDP > Accumulated Response of LGDP to LPAX

Both inequalities reinforce that responsiveness, both yearly and accumulated, of aviation demand is greater than that of GDP.

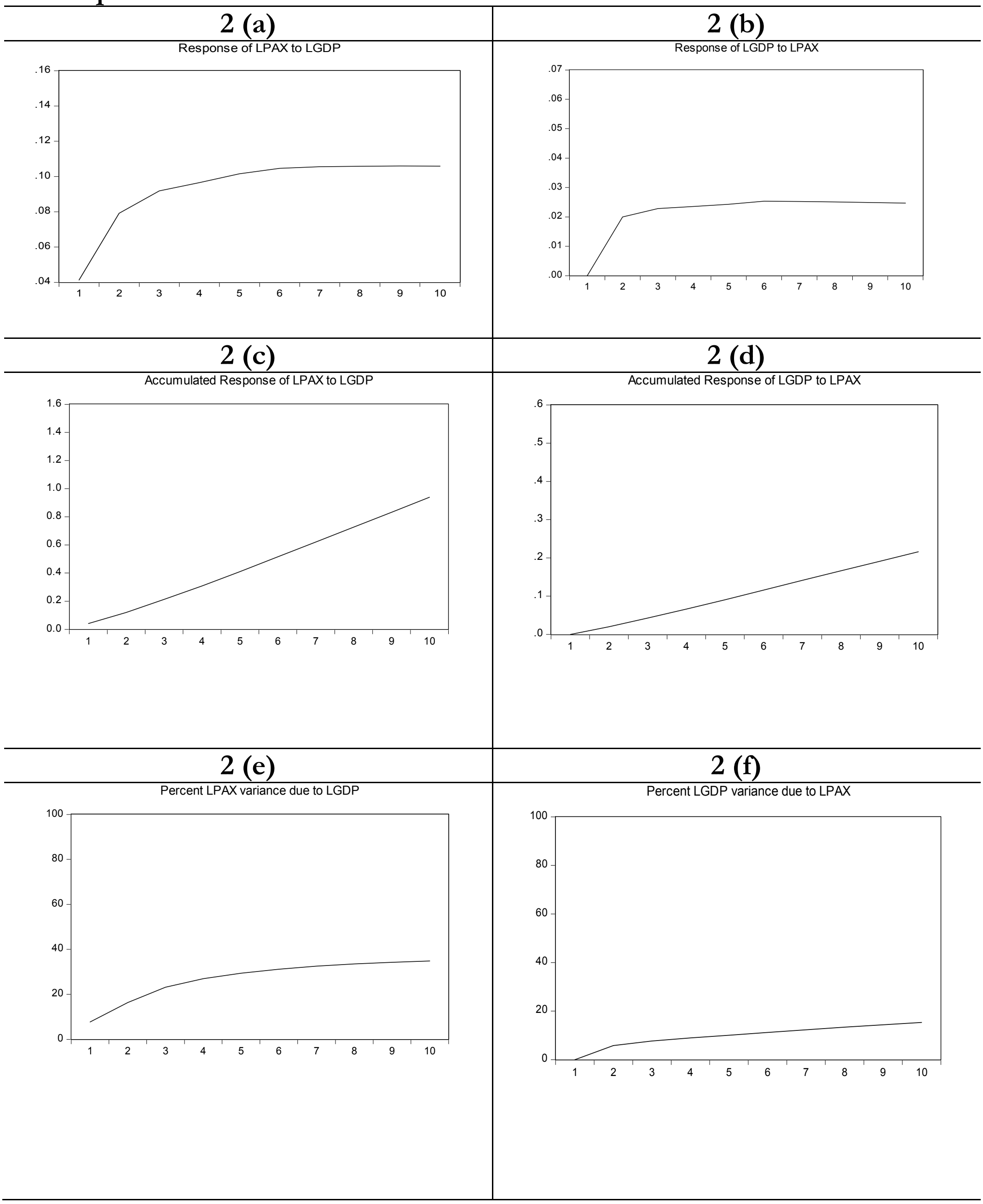
5.6. Forecasting Error Variance Decomposition (FEVD)

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 35% of LPAX forecasting error variance can be attributed to LGDP, whereas only 15% of LGDP forecasting error variance can be assigned to LPAX. Significant part of LPAX forecasting error variance explained by LGDP is in lines with IRF analysis furnished above. In comparative terms:

Variance of LPAX due to LGDP > Variance of LGDP due to LPAX.

Yuan et al. (2007) terms FEVD as an out-of-sample causality test.

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



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.

5.7. 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.[6]

$$X_t = \hat{\Gamma}'_{21} D_{1t} + \hat{\Gamma}'_{21} D_{1t} + \hat{\varepsilon}_t \qquad \textbf{(8)}$$

or directly from the difference regressions

$$\Delta X_t = \hat{\Gamma}'_{21} \Delta D_{1t} + \hat{\Gamma}'_{21} \Delta D_{1t} + \hat{u}_t \qquad \textbf{(9)}$$

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

$$y_t^* = y_t - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{u}_2 \qquad \textbf{(10)}$$

An estimated bias correction term

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

The FMOLS estimator is given by

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

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

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

Which may be interpreted as the estimated long-run variance of u_{1t} conditional on u_{2t}. We may, if desired, apply a degree-of-freedom correction to $\hat{\omega}_{1.2}$.

5.8. 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:

$$y_t = X_t'\beta + D_{1t}'\gamma_1 + \sum_{j=-q}^{r} \Delta X_{t+j}' \delta + v_{1t} \qquad \textbf{(14)}$$

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

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 $\theta = (\beta', \gamma')'$ have the same asymptotic distribution as those obtained from FMOLS and Conical Cointegration Regression (CCR).

An estimator of the asymptotic variance matrix of $\hat{\theta}$ may be computed by computing the usual OLS coefficient covariance, but replacing the usual estimator for the residual variance of υ_{1t} with an estimator of the long-run variance of the residuals. Alternately, you could compute a robust HAC estimator of the coefficient covariance matrix.

5.9. 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:

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

The matrix Ω can be represented as the following sum:

$$\boldsymbol{\Omega} = \boldsymbol{\Sigma} + \boldsymbol{\Gamma} + \boldsymbol{\Gamma}' \quad \textbf{(16)}$$

where

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

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

$$\boldsymbol{\Lambda} = \boldsymbol{\Sigma} + \boldsymbol{\Gamma} = (\boldsymbol{\Lambda}_1, \boldsymbol{\Lambda}_2) = \begin{bmatrix} \boldsymbol{\Lambda}_{11} & \boldsymbol{\Lambda}_{12} \\ \boldsymbol{\Lambda}_{21} & \boldsymbol{\Lambda}_{22} \end{bmatrix} \quad \textbf{(19)}$$

The transformed series is obtained as:

$$y_{2t}^{*} = y_{2t} - (\Sigma^{-1}\Lambda_2)' u_t \quad \textbf{(20)}$$

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

The canonical cointegration regression takes the following form:

$$y_{1t}^{*} = \beta' y_{2t}^{*} + u_{1t}^{*} \quad \textbf{(22)}$$

where

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

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}.

5.10. Comparison of the Cointegration Regression Estimates

Estimates of the three estimates techniques are summarized in the table 3:

Table 3. Comparison of the Cointegration Regression Estimates

Technique	Const.	Coefficient	t-statistics	S.E.	Adj. R^2	Long-Run Variance	Remarks on Relationship
FMOLS	14.0820	0.7343	5.0259	0.1461	0.2559	0.2310	positive & significant
DOLS	14.8236	0.6852	5.5402	0.1237	0.6718	0.1131	positive & significant
CCR	13.9089	0.7464	4.9859	0.1497	0.2620	0.2311	positive & 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 LPAX. However, DOLS has increased explanatory power of LPAX while the adjusted R^2 is highest using CCR. Our major concern, however, is to find the nature of relationship between LGDP and LPAX, that is found to be positive and significant using all three cointegration equation estimation techniques.

Table 4: Granger Causality Test Results

Null Hypothesis	F-Statistic
LGDP does not Granger Cause LPAX	0.9414
LPAX does not Granger Cause LGDP	3.2598**

Note: ** show statistical significance at 5%.

Results of Granger causality, in table 4, show that GDP does not have the tendency to boost the number of passengers carried (PAX) by aviation sector. While, PAX Granger-causes GDP. Increasing number of carried passengers contribute substantially to economic activity and increase GDP. Such is in lines with graphical evidence of 'aviation multiplier effect' in section 5.5 of this paper.

6. Conclusions

This paper investigated the cointegration, reaction to shocks and causality relationships between demand for aviation and economic growth in Romania. 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. LPAX reacts positively and strongly to a shock on LGDP. The maximum impact occurs after six years (t + 6) while LGDP also shows a substantial and quick positive reaction till second period and then sustained effect in coming years. This can be translated into a 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) and Mehmood & Kiani (2013).

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 Romania, 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 increase its macroeconomic contribution. The scope of research on aviation can be extended by using cross country analysis.

References

1. Bouzid, A. (2012), "The Relationship of Oil Prices and Economic Growth in Tunisia: A Vector Error Correction Model Analysis", Romanian Economic Journal, Vol. 15, No. 43, pp. 3-22.

2. Davidson, R., and MacKinnon, J. (1993), "Estimation and Inference in Econometrics", Oxford University Press, New York, NY.

3. Dickey, D., and Fuller, W. (1979), "Distributions of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association," Vol. 74, pp. 427–431.

4. Engle, R., and Granger, C. (1987), "Cointegration and Error Correction: Presentation, Estimation and Testing", Econometrica, Vol. 55, pp. 251–276.

5. Ghosh, S. (2006). "Steel Consumption and Economic Growth: Evidence from India", Resources Policy, Vol. 31, pp. 7-11.

6. Granger, C., and Newbold, P. (1974), "Spurious Regression in Econometrics", Journal of Econometrics, Vol. 26, No. 1, pp. 45–66.

7. IATA, (2008), "Air Transport Drives Economic and Social Progress: The Economic and Social Benefits of Air Transport 2008", Retrieved from http://www.iata.org/pressroom/Documents/atag_economic_social_benefits_2008.pdf

8. ICAO, (2006), "Manual on Air Traffic Forecasting," 3rd Ed.

9. Johansen, S., and Juselius, K. (1990), "Maximum likelihood Estimation and Inference on Cointegration with Application to the Demand for Money", Oxford Bulletin of Economics and Statistics, Vol. 52, pp. 162–211.

10. Maddala, G. (1992), "Introduction to Econometrics", 3rd Ed. McGraw-Hill, New York.

11. Marazzo, M., Scherre, R. and Fernandes, E. (2010), "Air Transport Demand and Economic Growth in Brazil: A Time Series Analysis", Transportation Research, Vol. 46, pp. 261–269.

12. Mehmood, B., Khan, A. and Khan, A. (2012), "Empirical Scrutiny of Demographic Dividend of Economic Growth: Time Series Evidence from Pakistan." Romanian Review of Social Sciences, Vol. 2, pp. 3-11.

13. Mehmood, B, and Kiani, K. (2013), "An Inquiry into Nexus between Demand for Aviation and Economic Growth in Pakistan", Academicia.

14. Morrison, S. A. (1983), "Estimation of Long-Run Prices and Investment Levels for Airport Runways", Research in Transportation Economics, Vol. 1, pp. 103-130.

15. Njegovan, N. (2004), "Are Shocks to Air Passenger Traffic Permanent or Transitory? Evidence from UK Data", Civil Aviation Authority, Economic Regulation Group.

16. Saher, N. (2011), "Impact of Oil Prices on Economic Growth and Exports Earning: In the Case of Pakistan and India", Romanian Economic Journal, Vol. 14, No. 40, pp. 117-151.

17. Yuan, J., Zhao, C., Yu, S., Hu, Z., (2007). "Electricity Consumption and Economic Growth in China: Cointegration and Co-feature Analysis", Energy Economics, Vol. 29, pp. 1179–1191.