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Catalyst Role of Indian Railways in Empowering Economy: Freight or Passenger Segment is on the Fast Track of Expansion or Exploitation?

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Abstract

Development of railways is important for the long run development of the country as it is sustainable both from logistics and cost to the economy aspects. However, at present the modal mix shows that railways are increasingly losing out to the road sector. The present research work examines the long run structural relationships of tonne-kilometer (TKM) and passenger-kilometer (PKM) for the freight and the passenger segments of railways with various economic variables in India. The authors make an attempt to understand the variables that affect the long run dynamics of this sector so that policy prescriptions are set in the correct perspective. Empirical analysis using cointegration and vector error correction analysis has been conducted and the relationship shows that there seems to be a long run relationship in TKM and PKM with the select economic variables. The adjustment mechanism for both the parameters is around 20-25%. The results also show that unlike our hypothesis, the industrial growth as captured by Index of Industrial Production does not granger causes our key parameter tonne-kilometer. The passenger-kilometer is however, determined by the gross domestic product and mineral oil price index.

Key words: *Indian Railways; Freight segment; Passenger segment; Passenger-kilometers; Tonnes-kilometers*

JEL Codes: *R1, R4, R5, Q4*

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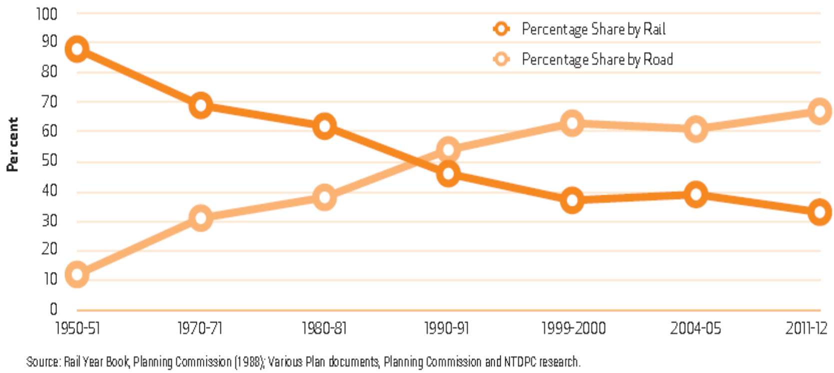
INTRODUCTION

Indian transport sector is considered one of the largest in the world, serving a land of 3.3 million kilometer and a population of more than 1.21 billion (TERI Energy & Environment data diary and Yearbook (TEDDY), 2014-15). To sustain India's current pace of economic growth, India needs an efficient and sustainable transport infrastructure. An efficient transport system, among other benefits, promotes specialization by providing a crucial link between the production and consumption of products at various locations. Adequate and good quality transport infrastructure plays an integral part in the growth of an economy. The strategic importance of the transport sector in India can be better understood from the fact that it alone contributes 6% to India's GDP (Statistics Times, 2015) and is the second highest energy consuming sector after industry (NITI Aayog, 2015). Then, there are also spillover effects that it creates, which generates a source of value for all other sectors.

In India, railways and roadways dominate the transport system in both passenger and freight traffic. However, this mix is developing at a suboptimal level, as railways are constantly losing out to roads. According to NTDPC (National Transport Development Policy Committee, Government of India, 2014), in freight traffic, railways share to total is consistently falling from 89% in 1950's to 30% in 2007-08, which is being clearly taken over by road transport. The graph below depicts the share of roads and rail in the total freight transport which portrays clear mirror-image overtime (Figure 1).

Figure 1: Modal Share of Railways and Roadways in Freight Transport in India, 1950-51 to 2011-12



The current inter-modal mix between rail and road is termed sub-optimal and is a cause of concern because railways are estimated to be around 6 times more energy-efficient and around 4 times more economical than the roadways. If we compute the environment and social sustainability of rail and roads then rails have an added advantage over energy consumption, financial costs, environmental damage and also overall social costs. The CO_2 emissions from railways are much lower than that of roadways in both freight and passenger segments (Table 1). However, despite these advantages of railways, there are various factors such as high freight rates and other constraints in generation of capacity because of which railways have not been able to meet the growing demand for transport. Instead, in the long run railways share should have been increasing.

Table 1: CO_2 emissions from Various Transport Modes in 2007-08

Freight Transport (gm/tkm)		Passenger Transport (gm/pkm)	
Road	160	Passenger Cars	175
Rail	29	Rail	75
Shipping	31	Airways	229

Source: 12th Five Year Plan, Government of India.

In India, railway operates with 19,000 trains a day, transporting 2.65 million tonnes of freight traffic and carries 23 million passengers daily (National Transport Development Policy Committee, Government of India, 2014). Railways are sustainable in terms of both logistics and cost to the economy. And it is also much more efficient especially for long distance routes. They are also a key in developing an integrated transport network with easy intermodal connectivity, which has become a necessity in the globalized world. There is enough evidence in favour of policy intervention to reverse the declining trend in railways share, both from a point of view of anticipated economic and environmental loss. The idea of creating Dedicated Freight Corridors (DFC) is actually seem to be an effective intervention to address some of the key issues in this sector. However, for long term development of the sector, careful planning and timely implementation of strategic decisions is essential in this regard.

The present paper is set up in this light to aim at assessing the key factors that determine long run performance of Indian railways. Attempt is made to focus on two crucial components of railways – passenger-kilometers (PKM) and tonne-kilometers (TKM). Both PKM and TKM are the performance indicators of rail transport for passenger and freight segment respectively. One of such attempts was made by (Ramanathan, 2001) for understanding the behavior of performance levels of the PKM and TKM in Indian railways sector. We will attempt to follow the approach followed in his paper to examine whether the results still hold true and to examine the literature and our results to see whether there is any explanation for deviation, if any. The main purpose of our paper is thus to understand the dynamics of PKM and TKM which can help us formulate more practical and feasible policy prescriptions for the railways sector so that its decline in modal share may be addressed. It is to be clearly noted that the present study has carefully made appropriate changes in variables and methodology so as to validate our robust results.

The details of the approach are being elaborated in the next section. Section 2 provides background and theoretical details of empirical methodology adopted. The Johanson Cointegration technique has been chosen to understand long run and short run performance of two railway parameters – PKM and TKM. Section 3,gives details about the selected model, data description and sources. Section 4 elaborates the results of the empirical exercise that have been presented and analysed for both PKM and TKM. Concluding remarks are made in the last Section.

METHODOLOGY FOR EMPIRICAL ANALYSIS

Econometrics provides a valuable tool for providing a relationship between macroeconomic variables. To understand the factors affecting both long run and short run performance of railways, various empirical analysis techniques can be resorted to. From running a simple time series regression to resorting to a Vector Auto-Regression (VAR) technique, there are various ways in which analysis can be done. These are however, restricted by the availability of data and in particular the nature of the data that limit the use of certain techniques.

Scope and Limitations

Keeping the objectives and limitations in mind, the concepts of cointegration and error correction have been selected for use in this paper to help us establish a long run relationship and short run adjustment mechanisms of the railway sector. This will help us form a relationship between transport performance and other macro-economic variables that can be further used for policy analysis. Since the model estimation of this paper revolves around time series modeling, based on popularity of use, EViews (version 7) software has been used for estimation. The primary interest of the study is to estimate PKM and TKM.

As will be explained in the upcoming sections, all our variables selected for analysis are non-stationary and hence a simple OLS analysis is not desirable as there are greater chances of the analysis leading to a spurious regression. One of the basic assumptions of OLS is that covariance between your dependent variable and your error term will never be zero, however this assumption is easily violated in a time series data. Running a regression would also mean that a large amount of information may be lost when the variables are used in their stationary form to become suitable for an OLS regression; the new coefficients may also not offer any meaningful interpretation after making them stationary. For example, a difference of difference of growth of industrial production makes hardly any sense for a meaningful interpretation.

In time series, there is a special case in which although the individual series may be non-stationary but there may be a possibility of existence of co-movement i.e. whenever the series drift apart in the long run there is a tendency for them to come back to a long run relation. This is termed as a cointegrating relationship. In more formal terms, variables are said to be cointegrated if each of the variables taken individually is non-stationary and integrated of order one i.e. I(1) with a presence of unit root, while the linear combinations of those variables are stationary i.e are integrated of order zero or I(0). Ramanathan (2001), have already established a cointegrating relation.

In econometrics, cointegration analysis is used in time series data to estimate and test stationary linear relations or cointegration relations between non-stationary time series variables. Cointegration analysis is particularly used when the series are assumed to have a long run equilibrium relationship. Cointegration analysis has also become important for the estimation of error correction model (ECM). The error correction refers to the adjustment process between the short run disequilibrium and a desired long run position. If variables are cointegrated, then there exists an error correction mechanism.

The testing for cointegration is based on the assumption that the variables included in the model need to be non-stationary of same order. For our analysis, hence we will first see whether the variable has a unit root. Time-series are generally non-stationary and unit root tests are useful to determine the order of the variables and provide the time series properties of the data. In order to verify the presence of unit root in the variables, we will use the popular Augmented Dickey Fuller (ADF) test. After identifying the series to be non-stationary, Engel Granger (1987) technique tests whether the linear combination is stationary to establish a cointegrating relation. Engel Granger technique is very simple to perform but has its own limitations, it can only identify one cointegrating relationship and since it is a two-step procedure any error in the first step are carried forward to the second step. Hence, this paper uses a superior method of Johansen's method for verifying the cointegration between variables. This method uses two likelihood-ratio test, the trace and the maximum eigenvalue statistics in order to determine the number of co-integrating vectors.

The methodology states that if the Trace Statistics and maximum Eigenvalues confirm the presence of one or more cointegrating variables, then it shows that there is an error correction mechanism which is needed. Thus, in the presence of cointegration, vector error correction may be used to show the direction of the relationship. Only when a cointegrating relation is identified can we resort to error correction model (ECM) to identify the short run mechanisms of adjustments to any shocks. In ECM , the short term dynamics of the variables in the system are influenced by the deviations from the equilibrium. It is a Modification of the VAR model to include cointegrated variables that balances the short-term dynamics of the system with long-term tendencies. Since we have a set of vectors of the variables in our study, we add the error correction term of each to the Vector Auto-Regression (VAR) which produces the Vector Error Correction Model (VECM). In VECM, variables are integrated of order one i.e. they are all I(1), the terms involving differences are stationary, leaving only the error-correction term to introduce long-term stochastic trends.

It is important to identify and determine the lag in the systems in the very beginning. For the entire exercise, we have determined the lag length using the most commonly used Akaike Information Criteria,

BASIC MODEL AND DATA DESCRIPTIONS

The paper tends to explore the presence of cointegrating relationships for two components of railway performance – PKM and TKM by using the methodology described above. Annual time-series data has been used for the period 1990-91 to 2013-14. The selection of variables in the study is based on various considerations. The expected impact of the variable, their data availability and their suitability for the cointegration analysis were the key concerns while choosing the variables. A comprehensive approach towards factors identification has been followed so as to identify factors that are crucial in affecting PKM and TKM. In our study we have shortlisted four variables in total which are considered as have factors impacting the performance of PKM and TKM in the country: These four variables are Gross Domestic Product, Index for Industrial Production, Mineral Oil Price Index and Urban Population growth rate. These are considered as some of the crucial variable which might affect a country's transport performance. Several other variables such as GDP of industrial sector, share of urban population in total population, total population, working group population, overall inflation etc. were also considered. These were however dropped since they were not found to be I(1) and instead their suitable and more relevant proxies were used. The details of the selected variables are discussed in the following paragraphs:

The data for Tonne Kilometer and Passenger Kilometer have been derived from the database maintained by the World Bank. The data for Gross Domestic Product at Constant Market Price (2004-05 base) and Index of Industrial Production (IIP) was taken from Central Statistical Office (CSO), Ministry of Statistics and Programme Implementation (MOSPI), and Government of India (GoI). The data for IIP was available on three bases: 1980-81, 1993-94 and 2004-05 and hence the index had to be spliced before it can be used for further analysis. Similarly, the data in Mineral Oil Price Index was available as 1980-91, 1993-94 and 2004-05 base and was taken from the Office of the Economic Adviser, Ministry of Commerce and Industry, Government of India and the index was spliced at a common base 1993-94. Urban Population Growth Rate data was taken from the World Bank database.

Two econometric models, one each for passenger segment and freight segment, has been specified to check for long run transport performance. The specification of the relationships is important before performing any cointegrating relation because incorrect lags, trends, constant etc. may affect the robustness of the results. Moreover, when performing an Engel Granger technique of cointegration, a regression specification is the first step to identify cointegrating relationship. Although, Engel Granger method is not used in this paper, the specifications are an easy way to describe the hypothesized relationship among the variables. All the variables are either used in natural logs or in terms of growth rates to maintain the consistency of econometric analysis. Description of the variables and their descriptive statistics is given in Appendix A and B.

Freight Segment: For the freight performance in railways, following cointegrating regression equation has been specified:

$$ln\_TKM_t = B_o + B_1\, ln\_IIP_t + B_2\, ln\_MIP_t + v_{tkm}$$

where,

TKM is Tonne Kilometer
IIP is Index of Industrial Production
MIP is Mineral Oil Price Index

The dependent variable; Tonne Kilometer which is the volume of goods transported by the railways, is measured in metric tons times kilometers travelled (World Bank). TKM is a crucial performance indicator for freight transport in railways.

Index of Industrial Production is an index which gives out growth of various sectors in an economy and comprises mainly of manufacturing, mining or construction. IIP being a short term indicator is expected to influence freight transport more quickly than the overall economic growth. This is also true because majority of the rail freight transport are bulk transport, the demand of which is captured nicely in the IIP data. A high industrial growth hence should lead to a positive effect on TKM. Similarly, as railways use more than one fuel, a mineral oil price index (MIP) is being used to represent the price variable. As the price index increases, it is expected that freight operations will fall.

Similarly, for the passenger mode the following model is being specified:

$$ln\_PKM_t = B_o + B_1\, ln\_GDP_t + B_2\, ln\_MIP + B_3\, URBANPOPGROWTH + v_{pkm}$$

where,

PKM is Passenger Kilometer
GDP is Gross Domestic Product of India
MIP is Mineral Oil Price Index
URBANPOPGROWTH is Urban Population Growth Rate

The dependent variable, Passenger Kilometers (PKM) is the number of passengers carried by railways times kilometers travelled. Indian Railways are the topmost rail passenger carrier (in terms of PKM) in the world. Passengers kilometer increased by 4.9% from 2011-12 to 2012-13, that is, from 1046.5 billion in 2011-12 to 1098.1 billion in 2012-13 (TERI Energy & Environment data diary and Yearbook (TEDDY), 2014-15).

GDP is the monetary value of final goods and services produced in a country in a given period of time. India's current rate of GDP is at around 7% and is considered to grow over the period of time. A positive relation between GDP and PKM is expected. As a country grows, more passengers are expected to travel. Railways being one of the important components of the transport sector, GDP should have a positive impact on PKM. The next parameter is urban population growth rate. As more motorized vehicles are concentrated in urban zone, taking urban population growth rate is considered as a more relevant for our analysis. India has a growing population and as the country's growth increases, it is expected more people will migrate to the urban areas as most of the industrial and services sectors are concentrafted in the urban conglomerates. . A high urban clustering is expected to increase the PKM. The term MIP has the same interpretation as in the freight model, and a negative relation with PKM is being expected.

Empirical Results and Interpretations

The two cointegrating relationships have been tested to check for the existence of a long run relationship between TKM, PKM and other selected variables. The results are presented and elaborated below in the following sessions. The results for freight segment of railways are more descriptive and are similarly replicated for passenger segment with less vigour.

Freight Segment

First, we have checked for stationarity using the Augmented Dickey Fuller (ADF) test. The ADF statistic is a negative number. The more negative it is, stronger the rejection of the hypothesis that there is a unit root at some level of confidence. For the freight segment, the ADF statistics at both 'level' and 'first difference' form suggest that all the three variables have a significant ADF at the first difference form and hence are integrated of order one, I (1). [Table 2]

Table 2: Augmented Dickey Fuller (Freight)

Variable Name	Level	1st Difference
LN TKM	1.193543 (0.9970)	(-)3.24575 (0.0307)**
LN MIP	(-)0.465675 (0.8812)	(-)4.9878 (0.0006)*
LN IIP	(-)0.22897 (0.9215)	(-)2.787769 (0.0763)***

Note: 1. Figures in parenthesis shows the p-value
2. * Significant at 1% level, ** significant at 5% level, *** significant at 10% level

As described in the methodology section, following OLS procedure in a time series data seems undesirable. One of the basic assumptions of OLS is that covariance between dependent variable and error term will never be zero, however this assumption is easily violated in a time series data. In such cases the results produced can be spurious when variables are non-stationary. Taking coginizant of this limitation we still have performed OLS to estimate the coefficientssince all variables are integrated of order one, their first difference forms are used to perform OLS estimation (Table 3).

Table 3: OLS Estimation (Freight)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LN_IIP)	0.649377	0.130577	4.973154	0.0001
D(LN_MIP)	-0.013071	0.070745	-0.184762	0.8552
R-squared	0.072445			
Akaike info criterion	-3.851399			

Result show that, the coefficient for index for industrial production (IIP) has statistically significant result at 1% level of significance with an expected positive sign. The coefficient of Mineral Oil Price Index which constitutes of oils such as petrol, high speed diesel used in railways has an expected negative relation. However, the relation is statistically insignificant. However it makes very little sense to rely on the significance or insignificance of the OLS procedure.

The lag selection criteria shows that for the Akaike Information Criteria the value is significant for lag length 4 and hence for all further analysis a lag length of 4 is being used.

Johonson cointegration tests were performed on the variables, the results of which are shown in Table 4. Both results using the Trace statistics and Maximum Eigenvalue are reported. The Null hypothesis for first row states is that there is presence of no cointegration. Using both trace and maximum eigenvalue this at most null hypothesis is rejected. We then proceed to the next row, where the null now is at most 1 cointegration relation, which gets rejected. The null for next row i.e. at most 2 cointegration relation however gets accepted. Thus, the model indicates the presence of two cointegrating equation.

Table 5 below depicts the normalized cointegrating coefficients to check whether the signs in the model are as expected or not. Due to normalization, the signs are reversed to enable proper interpretation. MIP and IIP both have the expected signs. A 1% increase in the price index of mineral will reduce the tonne kilometer by 0.86%. Similarly, increase in the value of Index of Industrial Production (IIP) as expected has a positive influence on freight transportation.

Table 4: Normalized Cointegrating Coefficients (Freight)

LN_TKM	LN_MIP	LN_IIP
1.0000	0.869330 (0.02792)	-2.042143 (0.03594)

Note: Standard errors in ( )

Taking into account that cointegrating relation is established, we then determine the error correction model that describes the short-run dynamics or adjustments of the cointegrated variables towards their equilibrium values. The vector-error correction model is employed with nonstationary series that are known to be cointegrated. The error correction term picks up any disequilibrium in the system and guides the variables of the system back to equilibrium. The results of the VECM model for freight data in table 6 shows that the error correction terms are both negative and less than one. In the first cointegrating equation, shows the speed of adjustment to any disequilibrium in the long-run relationship. The results show that around 20.6% of the disequilibrium in the long run relationship is corrected each year by changes in TKM. The value for this speed of adjustment comes out to be statistically significant.

Table 5: Vector Error Correction Statistics (Freight)

Error Correction:	D(LN_TKM)	D(LN_IIP)	D(LN_MIP)
CointEq1	-0.206416	0.210521	-0.36067
	(0.11320)/ [-1.82339]	*(0.09328)/ [2.25684]*	*(0.33389)/ [-1.08019]*
CointEq2	-0.202603	-0.324925	0.630991
	(0.13410)/ [-1.51085]	*(0.11050)/ [-2.94054]*	*(0.39552)/ [1.59535]*
D(LN_TKM(-1))	-0.214151	0.434266	-0.36768
	(0.27727)/ [-0.77236]	*(0.22847)/ [1.90075]*	*(0.81779)/ [-0.44960]*
D(LN_TKM(-2))	-0.06441	-0.087613	0.364601
	(0.29098)/ [-0.22136]	*(0.23977)/ [-0.36541]*	*(0.85822)/ [0.42483]*
D(LN_IIP(-1))	0.313333	0.157989	0.305523
	(0.28609)/ [1.09524]	*(0.23574)/ [0.67020]*	*(0.84380)/ [0.36208]*
D(LN_IIP(-2))	0.039132	0.058310	-1.10888
	(0.27365)/ [0.14300]	*(0.22549)/ [0.25859]*	*(0.80713)/ [-1.37386]*
D(LN_MIP(-1))	-0.218865	-0.043329	-0.03542
	(0.13455)/ [-1.62663]	*(0.11087)/ [-0.39081]*	*(0.39685)/ [-0.08924]*
D(LN_MIP(-2))	-0.091655	-0.117201	-0.19242
	(0.11510)/ [-0.79629]	*(0.09485)/ [-1.23571]*	*(0.33949)/ [-0.56680]*
C	0.066175	0.051284	0.173203
	(0.03338)/ [1.98243]	*(0.02751)/ [1.86446]*	*(0.09846)/ [1.75920]*

Standard errors in ( ) & t-statistics in [ ]

Further, to ensure robustness of the model, variance decomposition analysis has been conducted. It shows which component of the system shows the maximum variability. Table 7 below shows the results of the variance decomposition analysis. The results show that much of the variation in TKM is explained by TKM itself. In the medium run, however, the IIP and MIP also explain a significant amount of the variation (In the 5^{th} year, 54% of the variation is explained by TKM, 43% by IIP and 45% by MIP). Similar is the case to the variability arising in IIP and MIP. In the very short run, they both themselves explain their variability but in the medium run its impact on the other variables increases.

Table 7: Variance Decomposition Analysis (Freight)

Variance Decomposition of LN_TKM:				
Period	S.E.	LN_TKM	LN_IIP	LN_MIP
1	0.027846	100.0000	0.000000	0.000000
2	0.031951	98.53494	0.757922	0.707134
3	0.034570	86.14008	0.664226	13.19569
4	0.041126	65.86664	0.585629	33.54773
5	0.049481	54.34857	0.432051	45.21938
Variance Decomposition of LN_IIP:				
Period	S.E.	LN_TKM	LN_IIP	LN_MIP
1	0.022945	16.64990	83.35010	0.000000
2	0.037479	44.84130	54.36705	0.791653
3	0.043184	45.60623	53.54030	0.853473
4	0.046162	40.85440	49.90603	9.239576
5	0.053373	35.73866	40.02999	24.23134
Variance Decomposition of LN_MIP:				
Period	S.E.	LN_TKM	LN_IIP	LN_MIP
1	0.082129	34.73183	1.874637	63.39353
2	0.110704	37.87361	7.466561	54.65983
3	0.114761	36.09570	7.108609	56.79569
4	0.118741	36.83517	8.238105	54.92673
5	0.123139	34.86188	10.33461	54.80351
Cholesky Ordering: LN_TKM LN_IIP LN_MIP				

Granger's Causality can throw further light on the relationship between TKM, IIP and MIP. X is said to Granger cause Y if Y can be better predicted using the histories of both X and Y than it can by using the history of Y alone. The null hypothesis states that one variable does not granger causes the effect on other variable. Rejection of the null implies that there is granger causality. The results of Granger causality test in table 8 show that at 10% level of significance MIP granger cause IIP and at 1% level of significance TKM granger cause IIP. This is however, opposite to what was expected whereby IIP should granger cause TKM.

Table 8: Granger Causality (Freight)

Null Hypothesis:	F-Statistic	Prob.
LN_IIP does not Granger Cause LN_TKM	0.93581	0.4786
LN_TKM does not Granger Cause LN_IIP	5.92509*	0.0086
LN_MIP does not Granger Cause LN_TKM	1.86214	0.1874
LN_TKM does not Granger Cause LN_MIP	1.30661	0.3267
LN_MIP does not Granger Cause LN_IIP	3.09190***	0.062
LN_IIP does not Granger Cause LN_MIP	0.87844	0.5076

Note:* Significant at 1% level, ** significant at 5% level, *** significant at 10% level

Passenger Segment

The results of stationarity in table 9 shows that all considered variables are stationary at first difference i.e. they are integrated of order 1 or are I(1).

Table 9: Augmented Dickey Fuller (Passenger)

Variable Name	Level	1st Difference
LN MIP	(-)0.465675 (0.8812)	(-)4.9878 (0.0006)*
LN PKM	0.804249 (0.9918)	(-)3.073138 (0.0436)**
LN GDP	1.420123 (0.9984)	(-)4.238673 (0.0035)**
Urban Pop Growth	(-)1.646514 (0.4432)	(-)3.182717 (0.0349)**

Note: 1. Figures in parenthesis shows the p-value

2.* Significant at 1% level, ** significant at 5% level

The results of OLS regression on the stationary variables are presented in Table 10. Only GDP has a significant relationship on Passenger kilometer at 1% level of significance. The elasticity is 0.92, which explains one billion increases in GDP will increase the passenger kilometer elasticity by 0.92. Mineral Oil Price Index and urban population growth rate shows insignificant results. However, the signs of these coefficients are as expected. Both Mineral Oil price indexes and urban population growth rate have a positive coefficient sign. As explained in the freight mode, we should note that OLS estimation is not the appropriate procedure for estimation in time series data. So the significance and insignificance of results in OLS estimation may not show a true picture of the actual results.

Table 10: OLS Estimation (Passenger)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LN_GDP)	0.923026	0.173679	5.314555	0
D(LN_MIP)	-0.01748	0.090042	-0.19413	0.848
D(URBANPOPGROWTH)	0.18797	0.129134	1.455617	0.161
R-squared	0.194898			
AIC	-3.574449			

The lag length criteria using Akaike Information Criteria is significant here at zero lag for the model and hence all further results for passenger segment are performed using zero lag.

The next step is to check for cointegration in the passenger segment. In table 11 both trace and eigen value statistic indicate that there is 1 cointegrating equation. Therefore the null hypothesis which says that there is a presence of no cointegration is being rejected and the null hypothesis which says 'at most 1 cointegrating relationship' exists gets accepted.

Table 11: Unrestricted Cointegration Rank Test (Passenger)

Null Hypothesis	Eigen Value	Trace statistics	Prob.**
None *	0.773600	57.64515 (0.0046)	34.16542 (0.0062)
At most 1	0.573167	23.47973 (0.2233)	19.58135 (0.0812)
At most 2	0.130368	3.898384 (0.9116)	3.212756 (0.9316)
At most 3	0.029370	0.685628 (0.4077)	0.685628 (0.4077)

Note: * denotes rejection of the hypothesis at the 0.05 level

The normalized cointegrating coefficients of passenger-kilometers all show expected signs in Table 12 below. As explained in freight, signs in normalized cointegrating coefficients are reversed. . TKM and MIP have a negative relation, TKM and GDP and TKM and Urban Population Growth have positive signs.

Table 12: Normalized Cointegrating Coefficients (Passenger)

LN_PKM	LN_MIP	LN_GDP	URBANPOPGROWTH
1.0000	0.657816 (0.07071) [9.30299]	-2.06718 (0.11684) [-17.6924]	-0.583784 (0.08187) [-7.13045]

Note: Standard errors in ( ) and t statistics in [ ]

We, further, run the vector error correction mode to see the short run and long run effects of the variable. It can be seen from table 13, the error correction term PKM is negative and less than 1. It is also statistically significant at 10% level of significance. As explained in freight, negative ECM sign shows that our model seems to be converging and adjusting towards the short run equilibrium. The speed of adjustment in PKM is around 22.6%, which shows that around 22.6% of the variation in the disequilibrium in the system is corrected by changes in PKM.

Table 13: Vector Error Correction Model Statistics (Passenger)

Error Correction	D(LN_PKM)	D(LN_MIP)	D(LN_GDP)	D(URBANPOP GROWTH)
CointEq1	-0.225822	-0.378426	-0.006369	0.543472
	(0.12205)	(0.23642)	(0.07295)	(0.17589)
	[-1.85028]	[-1.60068]	[-0.08731]	[3.08977]
C	0.052038	0.101530	0.062031	-0.027521
	(0.00802)	(0.01553)	(0.00479)	(0.01156)
	[6.48957]	[6.53644]	[12.9428]	[-2.38139]

We further check for variance decomposition and found that majority of the variation in PKM, MIP and GDP is explained by these variables itself, which subsides little with time. Variation in urban growth rate in majority is explained by itself and PKM in period 1, but over time they subside and variation is more explained by MIP and GDP. PKM also shows visible variability due to variations in MIP and GDP. . The results of are presented below in table 14.

This is further verified using Granger Causality test. The results of Granger causality in table 15 show that MIP and GDP granger cause PKM at 5% and 1% significance level respectively. Also, at 10% level of significance PKM granger causes urban population growth and GDP granger cause MIP. Rest none of the variables seems to be causing the other variables.

Table 14: Variance Decomposition (Passenger)

Variance Decomposition of LN_PKM:					
Period	S.E.	LN_PKM	LN_MIP	LN_GDP	URBANPOPGROWTH
1	0.038456	100.0000	0.000000	0.000000	0.000000
2	0.059000	95.59180	2.413287	1.352414	0.642503
3	0.075139	93.22918	3.706710	2.077252	0.986859
4	0.088595	91.97622	4.392647	2.461654	1.169480
5	0.100304	91.23785	4.796869	2.688181	1.277098
Variance Decomposition of LN_MIP:					
Period	S.E.	LN_PKM	LN_MIP	LN_GDP	URBANPOPGROWTH
1	0.074493	22.28563	77.71437	0.000000	0.000000
2	0.095052	22.09366	75.74788	1.463285	0.695176
3	0.110436	21.85673	74.15992	2.700428	1.282916
4	0.123661	21.68503	73.08109	3.548200	1.685675
5	0.135551	21.56492	72.33784	4.133500	1.963738
Variance Decomposition of LN_GDP:					
Period	S.E.	LN_PKM	LN_MIP	LN_GDP	URBANPOPGROWTH
1	0.022985	12.77770	1.972709	85.24959	0.000000
2	0.032691	12.83114	2.112741	85.05445	0.001664
3	0.040148	12.85639	2.180007	84.96086	0.002749
4	0.046429	12.87017	2.216910	84.90953	0.003387
5	0.051957	12.87862	2.239572	84.87802	0.003786
Variance Decomposition of URBANPOPGROWTH:					
Period	S.E.	LN_PKM	LN_MIP	LN_GDP	URBANPOPGROWTH
1	0.055423	32.49713	8.234660	17.37276	41.89544
2	0.084316	20.05008	23.82990	29.57994	26.54007
3	0.107853	15.11742	30.34131	34.16985	20.37142
4	0.127578	12.73271	33.53526	36.35445	17.37758
5	0.144733	11.37192	35.36539	37.59540	15.66729
Cholesky Ordering: LN_PKM LN_MIP LN_GDP URBANPOPGROWTH					

Table 15: Granger Causality Test (Passenger)

Null Hypothesis:	F-Statistic	Prob.
LN_MIP does not Granger Cause LN_PKM	4.63793**	0.0247
LN_PKM does not Granger Cause LN_MIP	1.14327	0.3421
LN_GDP does not Granger Cause LN_PKM	10.1978*	0.0012
LN_PKM does not Granger Cause LN_GDP	0.04996	0.9514
URBANPOPGROWTH does not Granger Cause LN_PKM	0.29680	0.747
LN_PKM does not Granger Cause URBANPOPGROWTH	2.96530***	0.0786
LN_GDP does not Granger Cause LN_MIP	3.42868***	0.0561
LN_MIP does not Granger Cause LN_GDP	1.92613	0.1762
URBANPOPGROWTH does not Granger Cause LN_MIP	0.46194	0.6377
LN_MIP does not Granger Cause URBANPOPGROWTH	1.13547	0.3445
URBANPOPGROWTH does not Granger Cause LN_GDP	2.19757	0.1416
LN_GDP does not Granger Cause URBANPOPGROWTH	1.78983	0.1971

Note: * Significant at 1% level, ** significant at 5% level, *** significant at 10% level

CONCLUSION

The entire exercise of establishing the long run structural relationships of tonne-kilometer (TKM) and passenger-kilometer (PKM) for the freight and the passenger segments of railways with various economic variables showed some interesting results. The empirical exercise of cointegration shows that evidence of atmost one cointegrating relation was found in the freight segment, while atmost two cointegrating relation exists in passenger segment. This means that there is a long run relation that exists between IIP, MIP and TKM and also between MIP, GDP, urban population growth and PKM. Also, all the coefficients in the cointegrating equations have expected signs: IIP has a positive relation and MIP has negative relation with TKM; while GDP and urban population has positive while MIP has negative relation with PKM.

Further probing by Vector Error Correction model shows that the error correction term in both the models was significantly different from zero. It also came out to be negative and 'less than one' signifying a stable correction model. Results show that around 20-25 percent of disequilibrium in the long run relation is being corrected by the dependent parameter itself i.e. PKM and TKM.

Variance decomposition analysis shows that most of the variations in both PKM and TKM is explained by themselves. It is only in the medium run that a major share of variations in TKM is explained by IIP and MIP. The results also show that unlike our hypothesis, the industrial growth as captured by Index of Industrial Production does not granger causes our key parameter tonne-kilometer. Given that railways is the major mode for bulk commodity transport which forms a major part of index of industrial production, the causality was expected. Instead, the causality seems to run the other-way round – with TKM causing IIP. It is only in the PKM model that shows that the variations in IIP and GDP are explained by PKM which is also supported by the causality results. Both MIP and GDP granger cause PKM. In variance decomposition, the variations in urban population growth also seem to be explained by variation in PKM, though the causality test however seems to move in the unexpected direction.

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Appendix A
Description of Variables Used in Analysis

Description of Variables in TKM Model:	
Ln_TKM	Natural Log of Tonne Kilometer
Ln_IIP	Natural Log of Index of Industrial Production
Ln_MIP	Natural Log of Mineral Oil Price Index
Description of Variables in PKM Model:	
ln_PKM	Natural Log of Passenger-kilometer
ln_GDP	Natural Log of rate of growth of Gross Domestic Product of India
Ln_MIP	Natural Log of Mineral Oil Price Index
URBANPOPGROWTH	Urban Population Growth Rate

Appendix B
Descriptive Statistics of Variables Used

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
TKM	339187.3	281513	665810	158474	153448.8
IIP	210.004	176.6	373.4	91.6	98.38674
MIP	301.72	255	714	69	202.562
PKM	574023.3	490912	1158742	295644	263692.9
GDP	32077.61	27342.24	61958.42	14876.15	14959.09
URBANPOP GROWTH	2.668	2.667085	3.025237	2.392264	0.157061

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