Railways Augmented Production Function for European Union Countries

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Abstract

Transport and related infrastructure play a pivotal role in economic growth. It is especially important in case of European countries where efficient transport system allows to increase in international trade which stimulate economic growth. This study augments the empirical literature on transportation augmented neo-classical production function. It is done by introducing demand for railways into macro-production function of European Union. The data is collected from World Development Indicators for the period of 1985-2019. We apply both first and second generations of unit root test to examine stationarity and panel co-integration techniques to analyze long run relationship between national income and demand for railways. Robustness of tests is also done by using different estimators and country wise slopes. To detect the cause and effect, Granger and Dumitrescu-Hurlin causality tests are applied. Bi-directional causality between national income to demand for railways is found. Recommendations are made on the basis of empirical results.

1. Introduction

Role of infrastructure in an economy is well documented. One of the major building blocks of infrastructure is railways. Historically speaking, the railways has been part of revolution in mass transit. Specifically speaking, 1st (1800), 2nd (1850) and 4th (1950) Kondratiev waves were characterized by mass transit (Papenhausen, 2008; and Korotayev and Sergey, 2010). Railways is perhaps most versatile mode of transportation since it provides mass transit as well as passenger transportation. Contrary to airborne and seaborne transportation, Railways is not much prone to accidents of crash or sinking. For within country transportation on long routes, Railways is optimum mode of transportation.

In contemporary jargon, Railways is also known as 'Real Wide Web'. Railways is also considered as the backbone of urban transport. European Union (EU) started their struggle in the rail freight transport and passenger services sector from late 1960s because competition with the road and air-traffic was stiff. Therefore, railways adopted to new customer requirements. That is why railways became a popular mode of transportation. Via railways infrastructure, €1.06 million people got employment in 2012 (Source) and €66 billion were generated as value addition which is equivalent to 0.5% of GDP of European economy. The projects of rail infrastructure increase the size of the labor market, create more opportunities for the employees. It allows for networking between far-off areas within the country and may also results in mitigating regional disparity.

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Figure 1 portrays the mechanism through which railways contributes to national income.

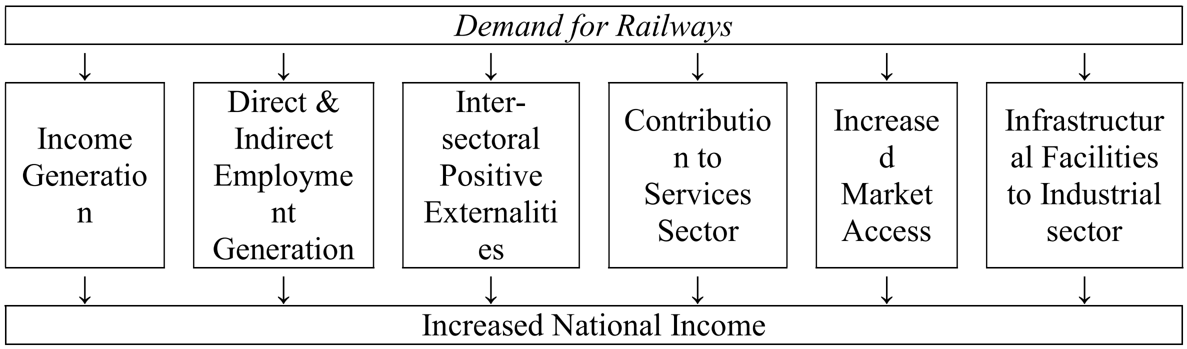

Figure 1: Mechanism of Contribution of Demand for Railways in National Income
Source**:** Authors' formulation

Based on the pictorial explanation in Figure 1, this paper attempts to quantify the relationship between demand for railways and national income in European Union. This study is organized as follows: section 2 demonstrates review of literature, section 3 covers methodology, whereas section 4 shows data sources, section 5 covers empirical analysis and section 6 concludes the study.

1.1 Hypothesis.
On the basis of objective following hypothesis will be tested:
H_A: There exists a causal and long run relationship between demand for railways and national income in European Union.
For affirming the contribution of this research, we review the existing research on this topic in the following section.

2. Literature Review

Empirical studies related to Railways are countable and are reviewed in this section. Hall (1993) discussed seven major forces which affected the structure of urban Europe. He argued that due to the Railways infrastructure, European economy developed its urban marketing and it bought socio-demographic changes.
Marten (2004) found that European Union had greater share in the trains and other public transport as compared to other personal vehicles. Givoni and Rietveld (2007) described the journey of railways and its role in the satisfaction of the passengers that used railways for travel. He focused on the journey of the railways in the Netherlands. First, he discussed the outlet modes on journey to and from railways stations, afterwards he examined that how a car effect on the choice to travel in the railways. Secondly, he emphasized and examined the passengers' satisfaction perception about the railways and about its journey. Then he estimated the overall perception of travelling by railways and found that good quality of railways stations and its facilities have important impact on the traveling by rails.
Friebel *et al.,* (2010) examined the railroad efficiency in Europe. He estimated the effects of reforms on the railways efficiency in Europe by applying production frontier model on panel data. The efficiency was found to increase when there was assessment of third - party

network, independence of regulator, and implementation of vertical separation. However, the reform effects also depended on sequencing where sequential reforms improved the efficiency.

Beria *et al.,* (2012) analyzed the railways regulation and liberalization in Italy, France, Germany and Spain. He analyzed the relationship between the state and the railways companies, network access systems by the operators. He also examined that how the public service requirements were financed, defined and regulated. He found that entry in the industry was not developed with its full potential.

Albalate *et al.,* (2015) discussed that with the advancement of the technology, new high-speed railways evolved. He examined that these high - speed rails had enormous influence on the air services. He compared both transportation modes and found that in some cases high speed rail and air transport had complementary relationship with each other. Mehmood *et al.,* (2015) investigated the role of air-transport in macroeconomic performance of Asian countries from 1970 to 2014. The salient feature of their research was the use of advanced econometric techniques to overcome issue of cross-sectional dependence Moreover, they found feedback effect between macroeconomic performance and air-transport.

Beenish *et al.,* (2016) discussed that railways had been the oldest means of transport. In their research work they examined the long run relationship between economic growth and demand for railways in Pakistan. They took time series data and applied co-integration techniques for long run analysis. They contributed to literature by using structural breaks by using Bai-Parron structural break test. Fully modified ordinary least squares (FMOLS) and Dynamic ordinary least squares (DOLS) techniques were employed to quantify the contribution of railways in economic growth of Pakistan. Granger causality test showed causality from economic growth towards demand for railways.

Review of studies reveal a gap for cross-country analysis for the nexus between demand for railways and national income. We choose European Union due to its remarkable industrial and infrastructural growth during last decades. This study overcomes the limitations of previous studies by including necessary control variables like capital and labor. In addition, robustness of the railways-growth nexus is conducted by using a number of econometric tests. Myszczyszyn and Mickiewicz (2019) studied the relationship between level of economic growth and the development of German Reich Railways. Empirical analysis was done on the basis of available dataset for the period 1872-1913 in case of Germany. To test this association several econometric models has been used such stationary test, Engle Granger Co-intergration test and Impulse response function. Results concluded that long relationship exist between development of railways and economic growth in Germany.

Wang *et al.,* (2020) investigated the impact of transport infrastructure such as railway and road on the economic growth of Belt and Road Initiative (BRI) countries. This study used cross study panel data from 2007 to 2016. Results concluded that at national level transport infrastructure plays an essential role in facilitating economic growth. Estimation also concluded that at regional level spatial spillover effects of transport infrastructure on economic growth is negative in case of East Asia, Central Asia, Common wealth independent states. Whereas there exists a positive spatial spillover effect of transport infrastructure on economic growth in central and eastern Europe counties.

Saidi *et al.,* (2020) examined the linkages between transport, logistic, Foreign Direct Investment, and economic growth in developing for the time period 2000-2016. A global panel divided developing countries into sub panels such as European and Central Asian

Countries, Middle East, North African, Sub Saharan, East Asia, Pacific and South Asian countries. Results of Generalized Moments of Average concluded that transport logistic infrastructure attracted FDI and contributed to economic growth.

Stanley (2020) examined the nexus between transport and economic growth in case of Nigerian economy. By using time series dataset for the period 1980 to 2018, results concluded that there exists a stable long relationship between transport system and economic development. Findings of error correction model showed that both transport sector output and investment in transport infrastructure have positive and significant impact on economic growth. Lenz *et al.,* (2018) find out the impact of transport infrastructure (rail and road) in economic growth in Central and Eastern European Member states during the time period 1995-2016. By adopting panel data estimates such as pooled ordinary least squares, fixed effect, random effects, finding reveals that there exists a negative relationship between railway infrastructure and economic growth because of negative and outdated railway infrastructure. Peterka (2020) determined the association between transport infrastructure and economic growth in case of 27 European Union member states for the time period 1995 to 2007. A production function approach was applied and results concluded positive impact of motorways and railway on the growth of GDP per capita.

3. Methodology

The testable prediction that Demand for railways and national income have nexus, is stated as follows:

$\boldsymbol{P_A}$: *There exists a long-run causal relationship between railways and macroeconomic performance.*

$$\boldsymbol{NI_{i,t} = f(RL_{i,t}, CP_{i,t}, LB_{i,t})}$$

Where

$\boldsymbol{NI_{i,t}}$ = GDP (constant 2005 US$).

$\boldsymbol{RL_{i,t}}$ = Railway, passenger carried (million passenger/km).

$\boldsymbol{CP_{i,t}}$ = Gross fixed capital formation.

$\boldsymbol{LB_{i,t}}$ = Labor Force.

$\boldsymbol{i}$ and $\boldsymbol{t}$ stand for cross-sections and time periods, respectively.

4. Data

4.1 Data Sources

From European Union, 25 countries are selected while the number of years is 35 (1985-2019) depending on the availability of data. Sample countries are Belgium, Bulgaria, Denmark, France, Germany, Estonia, Ireland, Greece, Spain, Croatia, Italy, Latvia, Lithuania, Luxembourg, Hungary, Netherland, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden and United Kingdom. Collection of data is done from World Development Indicators (WDI).

5. Empirical Analysis

5.1 Static Estimations

In order to examine the empirical relationship between demand for railways and national income, following analysis is conducted. We estimated static models namely; pooled OLS

(POLS), fixed effects (FE), random effects (RE) and first differenced fixed effect (FD). The estimated coefficients of demand for railways are statistically significant at 1% in POLS, FE, RE and FD estimations. The range of statistically significant coefficients is from 0.0424 to 0.1944 which is very close range. Control variables of capital and labour also show desirable signs of coefficient with statistical significance at 1% and 5%.

Table 1: Static Analysis – POLS, FE, RE and FD-FE Estimates

	POLS	*FE*	*RE*	*FD*
$RL_{i,t}$	0.0424^{a}	0.0424^{a}	0.0424^{a}	0.1944^{a}
	(0.012)	(0.012)	(0.012)	(0.064)
$CP_{i,t}$	0.6944^{a}	0.6944^{a}	0.6944^{a}	0.3758^{a}
	(0.020)	(0.020)	(0.020)	(0.059)
$LB_{i,t}$	0.2827^{a}	0.2827^{a}	0.2827^{a}	0.0548^{b}
	(0.020)	(0.020)	(0.020)	(0.022)
Constant	0.0002	0.0002	0.0002	0.0587^{a}
	(0.012)	(0.012)	(0.012)	(0.008)
Observations	875	875	875	850
Countries	25	25	25	25
CD‡	29.47^{a}	87.74^{b}	29.47^{a}	11.18^{a}

Notes: †: $NI_{it} = \alpha + \beta_{RL}.RL_{it} + \beta_{CP}.CP_{it} + \beta_{LB}.LB_{it} + \varepsilon_{it}$
††: $NI_{it} = \alpha_i + \beta_{RL}.RL'_{it} + \beta_{CP}.CP'_{it} + \beta_{LB}.LB'_{it} + \varepsilon_{it}$
†††: $NI_{it} = \alpha_i + \beta_{RL}.RL'_{it} + \beta_{CP}.CP'_{it} + \beta_{LB}.LB'_{it} + \beta_0 + \varepsilon_{it}$
††††: $NI_{it} = \beta_{RL}.\Delta RL'_{it} + \beta_{CP}.\Delta CP'_{it} + \beta_{LB}.\Delta LB'_{it} + \Delta\varepsilon_{it}$
‡ CD is the cross-sectional dependence test by Pesaran (2004) and is calculated as, $CD = \sqrt{\frac{TN(N-1)}{2}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$. [a] and [b] represent statistical significance at 1% and 5% whereas standard errors are in parentheses.

Source: Authors' estimates.

5.1 Dynamic Analysis

5.2.1 Unit Root Test Results.

Table 2 entails the results from the unit root tests applied to investigate stationarity in the series, selection of the appropriate lag length was made using the Schwarz Bayesian Information Criterion.

Table 2: Unit Root Tests

	NI_{it}	ΔNI_{it}	RL_{it}	ΔRL_{it}	CP_{it}	LB_{it}
IPS	-0.1567	-1.9523^{b}	3.6259	-9.4726^{a}	-1.9519^{b}	-1.5792^{c}
	NI_{it} is I(1)		RL_{it} is I(1)		CP_{it} is I(0)	LB_{it} is I(0)

Source: Authors' estimates.

5.2.2 Cointegration Tests

Results of IPS test in Table 2 show that NI_{it}, ST_{it}, CP_{it} and LB_{it} are showing a mixed order of integration, i.e. I(0) and I(1). Eberhardt and Teal (2010) suggest the use of macro-panel data techniques when time span is more than 20 years. Here t = 35, so we can resort to macro-panel data techniques. Since the series involved in our analysis are not integrated of same order, Pedroni and Kao tests cannot be applied. Therefore, we employ three econometric technique generation i.e. Mean Group (MG), Dynamic Fixed Effects (DFE) and Pooled Mean Group (PMG) to identify the appropriate sign and the size of the slope coefficient in the long run equation. Pesaran and Smith (1995) provided MG estimator of dynamic panels for large number of time observations and large number of groups. In this method separate equations are estimated for each group and the distribution of coefficients of these equations across groups is examined. It provides parameter estimates by taking means of coefficients calculated by separate equations for each group. It is one extreme of estimation because it just makes use of averaging in its estimation procedure. It does not consider any possibility of same parameters across groups. For MG estimator, each parameter is taken as:

$$\overline{\grave{u}_{\iota}} = \frac{1}{N} \sum_{i=1}^{N} u_i \qquad \overline{\grave{\theta}}_{\iota} = \frac{1}{N} \sum_{i=1}^{N} \theta_i \qquad \overline{\grave{\phi}_{\iota}} = \frac{1}{N} \sum_{i=1}^{N} \phi_i$$

For the averages of the parameters MG estimator will give consistent estimates. Thus allows all parameters to vary across countries, but it is not composed of the fact that certain parameters may be the same across groups.

Pesaran and Smith (1997) suggested PMG estimator of dynamic panels for large number of time observations and large number of groups. Pesaran et al., (1997, 1999) added further in PMG and extended it. Pooled mean group estimator considers both averaging and pooling in its estimation procedure, so it is considered as an intermediate estimator. PMG allows variation in the intercepts, short-run dynamics and error variances across the groups, but it does not allow long-run dynamics to differ across the groups. Adopting from Pesaran et al., (1997, 1999), PMG estimable model has an adjustment coefficient φ_i that is known as the error-correction term (ECT).

In fact, φ_i tells about how much adjustment occur in each period. In addition to MG and PMG, DFE is also used to estimate the cointegrating vector. DFE specification controls the country specific effects, estimated through least square dummy variable (LSDV) or generalized method of moment (GMM). DFE relies on pooling of cross-sections. Like the PMG, DFE estimator also restricts the coefficient of cointegrating vector to be equal across all panels.

Table 3: Dynamic Analysis – Cointegration Estimation

	Mean Group	*Dynamic Fixed Effects*	*Pooled Mean Group*
		Long Run Parameters	
RL_{it}	0.1511	0.4853[b]	0.0991[a]
	(1.014)	(0.227)	(0.016)
CP_{it}	0.7163[b]	0.2391	0.5851[a]
	(0.306)	(0.259)	(0.035)
LB_{it}	0.4718[c]	-0.1081	0.0272
	(0.276)	(0.247)	(0.054)
		Average Convergence Parameter	
φ_i	-0.2219[a]	-0.0652[a]	-0.0981[a]
	(0.053)	(0.024)	(0.023)
S.o.A	4.5 years	15.3 years	5.7 years
		Short Run Parameters	
ΔRL_{it}	-0.0521[b]	0.1404[a]	-0.1731[a]
	(0.026)	(0.016)	(0.051)
ΔCP_{it}	0.1489[a]	0.3112[a]	0.1886[a]
	(0.050)	(0.033)	(0.048)
ΔLB_{it}	0.1020[a]	0.0571[a]	0.1096[a]
	(0.024)	(0.021)	(0.033)
C	0.0446[a]	0.0573[a]	0.0575[a]
	(0.007)	(0.007)	(0.006)
Observations	850	850	850
Groups	25	25	25
p-value	$(\text{Hausman})_{MG/DFE} = 0.993$		
		$(\text{Hausman})_{MG/PMG} = 0.298$	
Remarks		PMG is efficient & consistent	
CD (MG)		20.44[a]	

Note: In parenthesis, standard errors of parameters are given while [a], [b] and [c] represent statistical significance at 1%, 5% and 10%, respectively. φ_i is the error correction term. S.o.A is the speed of adjustment. CD(MG) is the Pesaran (2004) test of cross-sectional dependence conducted on the residual of MG estimates.

Source: Authors' estimates.

Results in the Table 3 reveal the comparison of panel cointegration estimation using MG, DFE and PMG. All three alternative methods of cointegration (MG, DFE and PMG) show long run relationship between demand for railways and national income. It is evident from error correction terms (φ_i), which are less than unity and negative in terms of sign with statistical significance at 1% level of significance. However, the most efficient of the three estimators should be relied upon. Its selection is done by employing Hausman test. The results in Table 3 show statistical insignificance which implies superiority of PMG over MG and DFE. Therefore, railways-growth (dynamic) relationship is established under the assumption of absence of cross-sectional dependence.

5.3 Cross-Sectional Dependence

Results of CD test in Table 1 show the presence of cross-sectional dependence in the estimable model. Values of CD test are 29.47, 87.74, 29.47 and 11.18 for POLS, FE, RE and FD respectively. All are statistically significant at 1%, showing cross-sectional dependence (CD) in residuals of the estimable models. In real life, CD is due to reasons like oil price shock, global financial crisis and local spill over and is common in most of panels.

We examined the CD in residuals and variables using further tests. Friedman (1937) proposed a nonparametric test (R_{ave}) based on Spearman's rank correlation coefficient. It helps in determining cross-sectional dependence. One of the most well-known cross-section dependence diagnostics, is the Breusch-Pagan (1980) Lagrange Multiplier (LM) test statistic. Frees (1995) proposed a statistic (R^2_{ave}) which is based on the sum of the squared rank correlation coefficients. Pesaran (2004) proposed a standardized version of Breusch-Pagan LM test (LM_s), suitable for large N samples. Since (LM) and (LM_s) are likely to exhibit worsening size distortion for small T_{ij} for larger N, Pesaran (2004) proposed an alternative statistic (CD_P) based on the average of the pairwise correlation coefficients. This test is already used in Table 1. The null hypothesis of this test is cross-sectional independence against and Kao (2012) presented a simple asymptotic bias corrected scaled LM test (LM_{BC}).

In Table 4, six statistics are estimated to scrutinize the presence of cross-sectional dependence in residuals of estimable model. All are statistically significant at 1% supporting the assumption of cross-sectional dependence in the residuals of estimable model.

Table 4: Tests for Cross-Sectional Dependence in Residuals of Estimable Model

Test	*Statistic*	*Value*
R_{ave}	$\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}$	292.47[b]
LM	$\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}T_{ij}\hat{\rho}_{ij}^2 \rightarrow \chi^2\frac{N(N-1)}{2}$	2069.84[a]
R^2_{ave}	$\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}^2$	4.15[a]
LM_s	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2 - 1) \rightarrow N(0,1)$	72.25[a]
CD_P	$\sqrt{\frac{TN(N-1)}{2}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$	29.47[a]
LM_{BC}	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2 - 1) - \frac{N}{2(T-1)} \rightarrow N(0,1)$	71.89[a]

Note: [a] represents statistical significance at 1%.

Table 4 delves deeper by estimating four statistics, while considering the presence of cross-sectional dependence, in estimable model. All four tests are statistically significant at 1% showing cross-sectional dependence in the variables of estimable model.

Table 5: Tests for Cross-Sectional Dependence in Residuals of Estimable Model

		Value for:			
Test	*Statistic*	$NI_{i,t}$	$RL_{i,t}$	$CP_{i,t}$	$LB_{i,t}$
LM	$\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \rightarrow \chi^2 \frac{N(N-1)}{2}$	7885.1[a]	3469.2[a]	7327.3[a]	6210.4[a]
LM_S	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2 - 1) \rightarrow N(0,1)$	309.7[a]	129.4[a]	286.9[a]	241.3[a]
CD_P	$\sqrt{\frac{TN(N-1)}{2}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$	309.3[a]	129.0[a]	286.5[a]	240.9[a]
LM_{BC}	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2 - 1) - \frac{N}{2(T-1)} \rightarrow N(0,1)$	87.7[a]	33.4[a]	83.7[a]	77.3[a]

Note: [a] represents statistically significant at 1%.

Source: Author's estimates.

5.2 Stationarity Tests in Presence of Cross-sectional Dependence.

Cross-sectional dependence has a strong presence in residuals as tested in Table 4. It calls for checking stationarity using second generation of unit root tests since first generation of unit root tests (Im *et al.*, 2003) do not account for cross-sectional dependence in testing for stationarity.

Considering the evident cross-sectional dependence, we use second generation unit root tests proposed by Pesaran to shed light on the findings. Mathematically:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{i,t}$$

Where a_i is a deterministic term, $\bar{y}_t$ is the cross-sectional mean at time t and ρ is the lag order. $t_i(N,T)$ denotes the corresponding *t*-ratio of α_i and is known as cross-sectional ADF [CADF, attributed to Pesaran (2003)]. The average of the t-ratios gives the cross-sectional IPS [CIPS, attributed to Pesaran (2007)]. In Table 6, these tests are estimated with a constant term at level and first difference. Mutual consensus of both, CADF and CIPS tests, reveals variables are stationary at level and at first difference i.e. I(0) and I(1).

Table 6: Second Generation Unit Root Tests for Individual Variables

Cross-Sectional ADF (CADF)					
$NI_{i,t}$	$\Delta NI_{i,t}$	$RL_{i,t}$	$\Delta RL_{i,t}$	$CP_{i,t}$	$LB_{i,t}$
-1.619	-2.845[a]	-1.307	-4.686[a]	-2.772[a]	-3.186[a]
Cross-Sectional IPS (CIPS) Test					
$NI_{i,t}$	$\Delta NI_{i,t}$	$RL_{i,t}$	$\Delta RL_{i,t}$	$CP_{i,t}$	$LB_{i,t}$
-1.678	-2.853[a]	-1.735	-3.801[a]	-2.067[c]	-2.405[a]
$NI_{i,t}$ is I(1)		$RL_{i,t}$ is I(1)		$CP_{i,t}$ is I(0)	$LB_{i,t}$ is I(0)

Note: By definition: $CIPS = \frac{\sum_{i=1}^{N} t_i(N,T)}{N} = \frac{\sum_{i=1}^{N} CADF_i}{N}$

[a, c] represents statistically significant at 1%, 10% respectively

Source: Authors' estimates.

5.5 Dynamic Analysis with Cross-sectional Dependence

Dynamic analysis is suitable in case of relationships where current values of the explained variable are inclined by past ones. Growth regressions, such as in this paper, are mostly characterized by a lagged term of explained variable ($NI_{i,t-1}$).

In case of dynamic analysis, presence of CD requires implementation of improved versions of MG approach. From Table 1, CD tests have shown the presence of cross-sectional dependence in POLS, FE, RE and FD estimates. Therefore, it is logical to deploy estimation techniques that cater cross-sectional dependence. Pesaran (2006) forwarded Common Correlated Effects Mean Group (CCEMG) model with estimator $\beta_j(=\beta+\omega_j)$ which implies a common parameter β across the countries while ωj~IID(0,Vω). CCEMG has the tendency to asymptotically eliminate CD. Moreover, it allows heterogeneous slope coefficients across group members that are captured simply by taking the average of each country's coefficient.

Attributed to Eberhardt and Teal (2010), Augmented Mean Group (AMG) is a surrogate to CCEMG, which also captures the unobserved common effect in the model. Moreover, AMG estimator also measures the group-specific estimator and takes a simple average across the panel. The highlight of AMG is that it follows first difference OLS for pooled data and is augmented with year dummies.

In functional form, the estimable models can be rewritten as follows:

$$NI_{it} = \alpha_i + c_i t + d_i \hat{\mu}_t^{va\bullet} + \beta_{i,1}(RL_{i,t}) + \beta_{i,2}(CP_{i,t}) + \beta_{i,3}(LB_{i,t}) + \varepsilon_{i,t}$$

Where, i stands for cross-sectional dimension i = 1,…,n and time period t = 1,…,t and α_i represents country specific effects and $d_i t$ denotes heterogeneous country specific deterministic trends. α_i is related with the coefficient of respective independent variables $\beta_{i1} = \frac{\alpha_{i1}}{1-\alpha_{i1}}$, $\beta_{i2} = \frac{\alpha_{i2}}{1-\alpha_{i2}}$ and $\beta_{i2} = \frac{\alpha_{i2}}{1-\alpha_{i2}}$ that are considered as heterogeneous across the countries. It is also assumed that the short run dynamics and their adjustment towards long run take place via error term$u_{i,t}(=\acute{\Gamma}_i f_t + \varepsilon_{i,t})$. f_t Characterizes the vector of unobserved common shocks. f_t Can be either stationary or nonstationary, which does not influence the validity of the estimation (Kapetanios, Pesaran, and Yamagata, 2011). AMG estimation finds an explicit estimate for f_t which renders $\hat{\mu}_t^{va\bullet}$ (common dynamic process) economic meaningfulness. Total factor productivity (TFP) is one of the plausible interpretations of $\hat{\mu}_t^{va\bullet}$. Its coefficient d_i represents the implicit factor loading on common TFP. In addition, the cross-sectional specific errors $\varepsilon_{i,t}$ are permissible to be serially correlated over time and weakly dependent across the countries (Cavalcanti, Mohaddes, and Raissi, 2011). However, the regressors and unobserved common factor have to be identically distributed.

Table 7: Dynamic Analysis with Cross-Sectional Dependence

Estimator	*Common Correlated Effects Mean Group*		*Augment Mean Group*[†]			
Dependent variable	$\boldsymbol{NI_{i,t}}$	$\boldsymbol{NI_{i,t}}$	$\boldsymbol{NI_{i,t}}$	$\boldsymbol{NI_{i,t}}$	$\boldsymbol{NI_{i,t}-\hat{\mu}_t^{va\bullet}}$	$\boldsymbol{NI_{i,t}-\hat{\mu}_t^{va\bullet}}$
Trend Assumption	**WoT**	**WT**	**WoT**	**WT**	**WoT**	**WT**
$RL_{i,t}$	0.0768^{b} (0.034)	0.0844^{b} (0.040)	0.1642^{b} (0.073)	0.1224^{a} (0.036)	0.1480^{a} (0.046)	0.1095^{b} (0.050)
$CP_{i,t}$	0.4172^{a} (0.057)	0.4023^{a} (0.051)	0.4073^{a} (0.046)	0.3516^{a} (0.036)	0.2726^{a} (0.059)	0.3299^{a} (0.041)
$LB_{i,t}$	0.1877^{a} (0.050)	0.1893^{a} (0.049)	0.2033^{a} (0.050)	0.1801^{a} (0.048)	0.1528^{a} (0.052)	0.2010^{a} (0.041)
CDP	–	–	0.5495^{a} (0.140)	0.7701^{a} (0.191)	–	–
Country Trend	–	0.0172 (0.012)	–	-0.0003 (0.012)	–	-0.0158^{b} (0.007)
Constant	0.0005 (0.001)	-0.2921 (0.209)	-0.7815^{a} (0.201)	-1.0926 (0.126)	-1.4246^{a} (0.001)	-1.1554^{a} (0.113)
NST	–	15	–	16	–	10
RMSE	0.1249	0.1002	0.1617	0.1273	0.2034	0.1560
Observations	875	875	875	875	875	875
Groups	25	25	25	25	25	25
CD	-0.23	-0.73	3.60^{a}	-1.27	1.57	3.68^{a}

Notes: †: $NI_{it} = \alpha_i + c_i t + d_i\hat{\mu}_t^{va\bullet} + \beta_{i,1}(RL_{i,t}) + \beta_{i,2}(CP_{i,t}) + \beta_{i,3}(LB_{i,t}) + \varepsilon_{i,t}$
WoT and WT stand for estimation without and with country specific trends. CDP is the common dynamic process. In parenthesis, standard errors are given whereas [a] and [b] show statistical significance at 1% and 5% respectively. NST stand for Number of Significant Trends. RMSE stands for root mean squared error and uses residuals from group-specific regression.

Source: Authors' estimates.

5.5.1 Interpretation

The main variables of concern i.e. demand for railways ($RL_{i,t}$) has a statistically significant positive relationship with national income ($NI_{i,t}$) under augmented mean group (AMG) as well as under common correlated effects mean group (CCEMG) estimation. CCEMG is estimated with 'without and with country specific trend' assumption. Whereas AMG is estimated with an additional assumption of 'with and without common dynamic process (CDP)'. This allows for 4 variants of AMG. The significant positive relationship holds true for all variants 6 of CCEMG and AMG in Table 7. AMG being the most sophisticated is to be relied on.

5.6 Robustness Check

In Table 8, twenty-three (23) slopes are estimated using different estimators and their variants and compared in order to check the robustness of results of hypothesis. These include Pooled

Ordinary Least Squares (POLS), Fixed Effects (FE), Fixed Effects with Driscoll & Kraay standard errors (FE-DK), Random Effects (RE), Generalized Least Squares (GLS), First Differenced-Fixed Effects (FD), Fully Modified Ordinary Least Squares (FMOLS) with pooled, weighted pooled and group-mean estimation methods, Dynamic Ordinary Least Squares (DOLS) with pooled, weighted pooled and group-mean estimation methods, Difference Generalized Method of Moments (DIF-GMM), System Generalized Method of Moments (SYS-GMM), Dynamic Fixed Effects (DFE), Mean Group (MG), Pooled Mean Group (PMG), Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG).

CCEMG and AMG are further estimated with and without country specific trends. In addition, AMG is further estimated without common dynamic process under the assumptions of with and without country specific trends. In case of demand for railways, majority (87%) 20 out of 23 estimators give desirable results in terms of expected sign and statistical significance that adds to the robustness of the railways-growth nexus analyzed in this paper. Moreover, AMG – the most sophisticated of estimators – shows desirable results with all of its variants (with and without country specific trends and common dynamic process).

Table 8: Robustness Slope Parameters

Technique		*Statistic of Estimator*	*Value*	*S.E*
POLS		$\beta_{OLS} = (\sum_i X_i' X_i)^{-1}(\sum_i X_i' Y_i)$	0.0424[a]	0.012
FE		$\beta_{FE/DK} = \left(\sum_{i=1}^{N} X_i' Q X_i\right)^{-1}\left(\sum_{i=1}^{N} X_i' Q Y_i\right)$	0.0424[a]	0.012
FE-DK			0.0424[c]	0.024
RE		$\beta_{RE/GLS} = \left(\sum_{i=1}^{N} X_i'\Omega_M^{-1} X_i\right)^{-1}\left(\sum_{i=1}^{N} X_i'\Omega_M^{-1} Y_i\right)$	0.0424[a]	0.012
RE-GLS			0.0421[a]	0.009
FD		$\beta_{FD} = (\Delta X'\Delta X)^{-1}\Delta X'\Delta Y$	0.1944[a]	0.064
FMOLS	FP	$\beta_{FP} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}X_{it}'\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_{it}\bar{Y}_{it}^{+} - \lambda_{12}^{+\prime}\right)$	0.0136	0.018
	FW	$\beta_{FW} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \bar{X}_{it}^{*}\bar{X}_{it}^{*\prime}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{X}_{it}^{*}\bar{Y}_{it}^{*} - \lambda_{12i}^{*\prime}\right)$	0.0604[a]	0.014
	GM	$\beta_{FG} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\sum_{t=1}^{T}\bar{X}_{it}\bar{X}_{it}'\right)^{-1}\sum_{t=1}^{T}\left(\bar{X}_{it}\bar{Y}_{it} - \lambda_{12i}'\right)\right\}$	0.1267[a]	0.017
DOLS	FP	$\begin{bmatrix}\beta_{DP}\\ \gamma_{DP}\end{bmatrix} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\bar{W}_{it}\bar{W}_{it}'\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\bar{W}_{it}\bar{Y}_{it}'\right)$	-0.0030	0.024

	FW	$\begin{bmatrix}\beta_{DW}\\ \gamma_{DW}\end{bmatrix} = \left(\sum_{i=1}^{N}\widehat{\omega}_{1.2i}^{-1}\sum_{t=1}^{T}\overline{W}_{it}\overline{W}_{it}{}'\right)^{-1}\left(\sum_{i=1}^{N}\widehat{\omega}_{1.2i}^{-1}\sum_{t=1}^{T}\overline{W}_{it}\overline{Y}_{it}{}'\right)$	0.0116[a]	0.008
	GM	$\begin{bmatrix}\beta_{DG}\\ \gamma_{DG}\end{bmatrix} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\sum_{t=1}^{T}\overline{W}_{it}\overline{W}_{it}{}'\right)^{-1}\sum_{t=1}^{T}\overline{W}_{it}\overline{Y}_{it}{}'\right\}$	0.1129[b]	0.046
DIF-GMM			0.1153[a]	0.006
SYS-GMM			0.0789[a]	0.005
DFE		$\beta_{DFE} = \left(\sum_{i=1}^{N} X_{i,t-1}'QX_{i,t-1}\right)^{-1}\left(\sum_{i=1}^{N} X_{i,t-1}'QY_i\right)$	0.4853[b]	0.227
MG		$\beta_{MG} = \frac{1}{N}\sum_{i=1}^{N}\theta_i$	0.1511	1.014
PMG		$\beta_{PMG} = -\left(\sum_{i=1}^{N}\frac{\widehat{\phi}_i^2}{\widehat{\sigma}_i^2}X_i{}'H_iX_i\right)^{-1}\left\{\sum_{i=1}^{N}\frac{\widehat{\phi}_i}{\widehat{\sigma}_i^2}X_i{}'H_i\left(\Delta Y_i - \widehat{\phi}_i Y_{i,t-1}\right)\right\}$	0.0991[a]	0.016
CCEMG	WoT	$\beta_{CCEMG} = J^{-1}\sum_{i=1}^{J}\hat{\beta}_j$	0.0768[b]	0.034
	WT		0.0844[b]	0.040
AMG	$(WoT)_{CDP}$	$\beta_{AMG} = \frac{\alpha_{i1}}{1-\alpha_{i1}}$	0.1642[b]	0.073
	$(WT)_{CDP}$		0.1224[a]	0.036
	WoT		0.1480[a]	0.046
	WT		0.1095[b]	0.050

Notes: FP, FW, FG stand for Pooled, Weighted Pooled and Group-Mean estimation methods. $(WoT)_{CDP}$ and $(WT)_{CDP}$ show estimates with explicit common dynamic process 'without trend' and 'with trend' argument. FE-DK, GLS, DIF-GMM and SYS-GMM represent Fixed Effects with Driscoll and Kraay standard errors, Generalized Least Squares, Difference Generalized Method of Moments and System Generalized Method of Moments, respectively. WoT and WT show estimates without common dynamic process 'without trend' and 'with trend' argument. [a] and [b] show statistical significance at 1% and 5%, respectively. S.E stands for standard error.

Source: Authors' estimates.

5.7 Impetus of Relationship

At country level, robustness of the results is also affirmed by estimating country specific slopes. Majority of countries show highly significant positive relationship between demand for railways and national income. Whereas remaining countries either give unexpected sign and/or statistical insignificance.

In similar veins, country specific error terms are also estimated. Ones listed in the Table 9 fulfill the following conditions:

$ECT_i < 1, |ECT_i| > 0$ And $(p - value)_{ECT_i} < 0.05$.

These countries are major contributors to overall statistically significant long run relationship.

Table 9: Robustness Slope Parameters

		Country Specific Slopes (θ_i)			
Country	θ_i	*S.E*	*Country*	θ_i	*S.E*
Belgium	0.0702[b]	0.028	Luxembourg	1.3979[a]	0.119
France	0.0769[a]	0.026	Hungary	0.5464[a]	0.191
Germany	0.1518[a]	0.033	Netherland	0.1411[a]	0.029
Ireland	0.3172[a]	0.077	Austria	0.4837[a]	0.049
Greece	0.3075[a]	0.075	Poland	0.4837[a]	0.049
Spain	0.5227[a]	0.041	Portugal	0.2565[b]	0.105
Italy	0.2806[a]	0.043	Romania	1.8394[a]	0.112
Latvia	0.6060[a]	0.119	Slovakia	0.3651[a]	0.038
Lithuania	0.4954[b]	0.225	Finland	0.4917[a]	0.047

	Country Specific Error Correction Terms (ECT_i)		
Country	ECT_i	*Country*	ECT_i
Bulgaria	-0.2564[a]	Hungary	-0.0952[a]
Germany	-0.0383[a]	Portugal	-0.0822[a]
Estonia	-0.2524[a]	Slovakia	-0.0613[a]
Ireland	-0.0174[a]	Finland	-0.0976[a]
Greece	-0.1641[a]	Sweden	-0.0405[a]
Croatia	-0.1987[a]	United Kingdom	-0.0427[a]
Latvia	-0.0380[a]	–	–

Note: $\theta_i = \frac{\delta_i}{1-\lambda_i}$, [a] show statistical significance at 1%. S.E stands for standard error. ECT_i are the country specific error correction terms.

Source: Authors' estimates.

Countries including Bulgaria, Finland, Germany, Greece, Hungary, Ireland, Latvia, Portugal and Slovakia show both expected significant slope as well as country specific significant ECT. These countries contribute to the overall positive sign and significance of relationship between demand for railways and national income.

5.8 What Causes What?

5.8.1 Panel Granger Causality Test

Work of Granger (1969) laid the foundation of causality test that uses the bivariate regressions in a panel data context:

$$y_{i,t} = \alpha_{0,i} + \alpha_{1,i}\, y_{i,t-1} + \cdots + \alpha_{p,i}\, y_{i,t-p} + \beta_{1,i}\, x_{i,t-1} + \cdots + \beta_{p,i}\, x_{i,t-p} + \epsilon_{i,t}$$

$$x_{j,t} = \alpha_{0,j} + \alpha_{1,j}\, x_{j,t-1} + \cdots + \alpha_{p,j}\, y_{j,t-p} + \beta_{1,j}\, y_{j,t-1} + \cdots + \beta_{p,j}\, y_{j,t-p} + \varepsilon_{j,t}$$

Depending on the assumptions about homogeneity of the coefficients across cross-sections, there are two forms of panel causality test. First and conventional type treats the panel data as one large stacked set of data and performs the causality test in the standard way, that assumes all coefficients same across all cross-sections.

$$\alpha_{0,i} = \alpha_{0,j}, \alpha_{1,i} = \alpha_{1,j}, \dots, \alpha_{p,i} = \alpha_{p,i}, \forall_{i,j}$$
$$\beta_{1,i} = \beta_{1,j}, \dots, \beta_{p,i} = \beta_{p,i}, \forall_{i,j}$$

Table 10: Panel Granger Causality Test Results

Causality	*F-Statistic*	*Remarks*
$RL_{i,t} \rightarrow NI_{i,t}$	60.546[a]	Bi-causal Relationship between railways and macroeconomic performance (Feedback effect hypothesis holds).
$NI_{i,t} \rightarrow RL_{i,t}$	18.729[a]	

Source: Authors' estimates.

Results of panel Granger causality are shown in Table 10.
Bi-causality between demand for railways and national income is evident from results in Table 10. Feedback effect hypothesis gets support for statistical significance of F-statistics. The mechanism of causality from demand for railways to national income gets support from Figure 1. However, causality from demand for railways to national income gets support from Beenish et al. (2016).
Figure 2 portrays the feedback effect hypothesis between demand for railways and national income. Learning from Percoco (2010) and Mehmood, Aleem and Shahzad (2015), we sequentially categorized the effects of demand for railways as direct, indirect, induced and catalytic impacts.

$$\boxed{Increased\ National\ income} \longrightarrow \boxed{Direct\ \&\ Indirect\ employment\ generation} \longrightarrow$$
$$\boxed{Income\ generation} \longrightarrow \boxed{Increased\ demand\ for\ Railways} \longrightarrow$$
$$\boxed{Railways\ infrastructure\ development} \longrightarrow \boxed{Direct\ effects} \longrightarrow$$
$$\boxed{Indirect\ effects} \longrightarrow \boxed{Induced\ effects} \longrightarrow \boxed{Catalytic\ effects} \longrightarrow$$
$$\boxed{Increased\ National\ income}$$

Figure 2: Feedback Hypothesis for Railways and National income.
Source: Authors' formulation.

5.8.2 Rationale for Dumitrescu-Hurlin Causality

One of the main issues specific to panel data models refers to the specification of the heterogeneity between cross-sections. To consider the heterogeneity across cross-sections, Dumitrescu-Hurlin (2012) made an assumption of allowing all coefficients to be different across cross-sections. In addition to presence of heterogeneity among cross-sections, if cross-sectional dependence exists in panel, Dumitrescu-Hurlin causality is suitable. Results of CD tests in Table 1, Table 3, Table 4 and Table 5 show the presence of cross-sectional dependence. Whereas, stationarity is a basic requirement of Dumitrescu-Hurlin causality test.

Second generation unit root test named as Pesaran's CADF (2003) and CIPS (2007) statistic fulfills the objective of checking for stationarity in presence of cross-sectional dependence. Therefore, Dumitrescu-Hurlin causality test should be applied. Its results are as follows:

Table 11: Dumitrescu-Hurlin Causality Test Results

Causality	$W_{N,T}^{HNC}$	$\tilde{Z}_N^{HNC}$	*p-value*	*Remarks*
$RL_{i,t} \rightarrow NI_{i,t}$	4.870	27.331	0.000	Homogeneous Bi-causal relationship between railways and macroeconomic performance.
$NI_{i,t} \rightarrow RL_{i,t}$	4.506	5.056	0.000	

Source: Authors' estimates.

Table 11 shows statistical significance of first $\tilde{Z}_N^{HNC}$ test statistics which shows that both null hypotheses are rejected. It implies that that $RL_{i,t}$ and $NI_{i,t}$ homogeneously cause each other. Homogenous causality from national income to demand for railway can be attributed to 'uniform growth effects' of economic growth on demand for railways. However, homogenous causality from demand for railways to national income can be attributed to similar organizational structures, networking among intercountry railways and homogenous standards due to membership of a single union (EU).

6. Conclusion

This study investigated the hypothesis that railways-growth nexus in the context of European Union. Previous empirical literature based on impact of railways on national income is confined to time series analysis. But here, the cross-country analysis along with provision of effects of spillover and shocks renders the analysis of nexus more detailed. Moreover, previous findings are affirmed via inclusion of control variables, broader cross-sectional dimension. Findings of this study are in conformity to Beenish, Mehmood, Saleem and Yasar (2016), expect for causality which was uni-causal in case of Pakistan. Here causality is bi-causal shows presence of feedback effect. It is due to mature and well-functioning railways sector in European Union.

Feedback effect is also found, which shows that increased national income has a favorable effect on railways. Increased individual income encourages people to demand more for railways for travel within the country. The feedback effect can be explicated in analogy to 'multiplier-accelerator effect'. This concept, attributed to Samuelson (1939), advocates the effect of increased national income on investment and vice versa. However, we learn from Mehmood, Aleem and Shahzad (2015) to coin the term 'railways multiplier-accelerator effect'.

Further research can be done on efficiency of railways of individual countries. Especially country case studies should be conducted for sample countries that have not shown significant positive relationship in country specific analysis in this paper. Within EU, the standards should be homogenized to gain from the positive externalities of network effects.

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