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Analysis of convergence in transport infrastructure: a global evidence

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This study investigates the convergence in transport infrastructure for 102 countries spanning 1990-2018 using Phillips and Sul econometric methodology. We constructed a transportation infrastructure by a composite index of transportation computed via principal component analysis (PCA). Our findings suggest the presence of panel convergence at the global level, while the income groups exhibited panel divergence. The results obtained from the iterative testing procedure suggest that the sub-groups exhibited convergence and divergence features. Overall, this study finds that the process of convergence in transportation reflects the desirable emanations of transportation policies sharing possible similar characteristics, at least to some extent, across the globe.

Keywords: *transportation convergence, transition patterns, principal component analysis, income groupings.*

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1. Introduction

This study focuses on convergence in global and income group of countries transport infrastructural development. Global convergence in transportation infrastructures simply implies that countries across the globe are moving towards attaining the same level of transport infrastructural development. How true this convergence is in transportation, remains a question that deserves an answer through empirical investigation. This is because many countries across the globe are faced with different challenges that impede their rapid progress in transport infrastructural development. For example, Schuckmann et al.'s (2012) study identified the factors which will influence the future development of the transport infrastructure until the year 2030 across the globe. And these include intensified globalisation, increased urbanisation, ongoing shortages in public finances, and the requirements of a more demanding and growing world population are some of the challenges, which global transport will face. The study further identifies, assesses, and integrates long-range developments of various factors, such as supply and demand, financing, competitiveness, and sustainability, which will affect the future of the transport industry and its infrastructure.

Despite the past, present and future anticipated challenges in the sector, the global transportation industry over the years in both developed and less developed countries has undergone tremendous change due to investment, information sharing, privatisation and deregulation, evolving technological capabilities and increased competition. This is one of the reasons the transportation sector across the globe has witnessed some level of progress. Even though the world has experienced some level of transport infrastructural development, many countries still have the problem of optimising and maximising its utilisation for quality life, profit, and advancement of the economy. As a result, global transportation in terms of availability, accessibility and usage have been put into consideration globally (Schuckmann et al., 2012). Given the role that the transportation sector plays in an economy, it has become a vital subject of discourse among several national/international policymakers, global communities and international organisations (World Energy Council (WEC), 2007; Organisation for Economic Co-operation and Development (OECD), 2006; International Transportation Forum (ITF), 2012). It was on this basis that Beyzatlar and Yetkiner (2017) examined the convergence in transportation measures across the EU-15 countries by using several control variables that may have the potential to affect transportation convergence, namely GDP per capita, trade openness, urbanisation and inward foreign direct investment stock.

There are several important rationales for testing for convergence in transportation. Inferences from testing the convergence of transportation can be used to determine whether a target set for the transportation sector, especially in terms of transport infrastructural development, will be realised. Another importance of testing for convergence of transportation is that it will allow scholars to know whether idiosyncratic country-specific factors such as economic structure, institutional factors, socioeconomic conditions and efficiency of the transportation sector can explain the differences in the level of transport infrastructural development. Whenever there is convergence in transportation, it means idiosyncratic country-specific factors might not significantly explain the differences in the transportation infrastructures across countries. Moreover, a uniform policy at the income group level might/might not be sufficient to realise a particular level of transportation infrastructures. The existence of convergence could also be evidence that the concept of a security web in transportation may exist. In this sense, the concept of a security web implies that a country usually sees its neighbouring countries advancement in transport infrastructures as a challenge. Thus, any improvement in transport infrastructural development in neighbouring countries will influence the transport infrastructural development of a country. In cases where countries try to match the level of transport infrastructural development of others, the likelihood of taking advantage could tend to be usually reduced and minimised. This study is also important because it will inform national/international policymakers, global communities and international organisations on the gaps in transport infrastructure amongst countries globally, and the need to bridge the gaps and formulate appropriate policies to encourage catch-up.

Due to the limited number of studies on the convergence in transportation, conceptual and methodological approaches are yet to be extensively explored. Therefore, this article contributes to the literature in a number of ways: (i) compared to some previous studies that have utilised a dynamic panel model to examine convergence in transportation (Beyzatlar & Yetkiner, 2017), this study utilised the methodological approach proposed by Phillips and Sul (2007, 2009) because of the following advantages it has over other methodological approaches. First, it does not start from the specific assumption that the stationarity of the variables and/or the presence of common factors are necessary. Second, it is based on a general form of nonlinear time-varying factor models. Third, it assimilates the possibilities of transition heterogeneity or transition divergence. Fourth, it helps to identify the existence of club convergence or clusters in which different convergence paths can be distinguished among heterogeneous economies involved in a convergence process. Fifth, this study applied the Phillips and Sul (2009) methodology which helps in merging clubs when the clustering procedure tends to overestimate the number of clubs above their true number. Beyzatlar & Yetkiner's (2017) study fail to apply this methodology. Therefore, the importance of this study for the transportation literature is that it provides a more robust analysis by applying the Phillips and Sul (2007, 2009) methodology.

(ii) while some studies investigate the determinants of transportation infrastructure and examine the transportation infrastructure between rich and poor countries, to the best of our knowledge no study has examined the convergence of transportation infrastructures (defined as air transport, freight (AIRT), roads total network kilometers (km) (RNWS), and rail lines (total route- kilometers (km)) (RALI)) at the global and income group levels, namely, low (LIC), lower-middle (LMIC), upper-middle (UMIC), and high-income countries (HIC). We based the disaggregation of our data on Gross National Income (GNI) per capita, calculated using the World Bank Atlas method. This is pertinent because income group levels of transportation infrastructure could either widen or contract the existing economic, employment, poverty and social inequalities (Boarnet, 1995; Yu, 2012; Agbelie, 2014; Beyzatlar & Yetkiner, 2017; Benevenuto & Caulfield, 2019; Pasha et al., 2020). Therefore, if countries at the global and income group levels are catching up with one another it implies that the gap in transportation infrastructure is gradually reducing, and consequently, it will reduce the levels of economic, poverty and inequality among countries.

(iii) In this study, the reason we grouped the countries into respective income groups and tested for club convergence, include: firstly, convergence clubs can be useful in making comparisons and inspecting the development of one income group with reference to another income group (or identifying groups of countries within each income group that converge to different equilibria, allowing individual countries to diverge); and within all these groups, we could identify the similarities or differences between countries within income groups, and either generalise or make specific inferences (Bernard & Durlauf, 1995). Reasons why countries not belonging to any convergence group have diverged could be identified, thereby enabling us to shed more light on the possible factors behind the similarities or differences in transportation infrastructure among the income groups. Secondly, given that the data used for this study comprised 102 countries with different levels of transport infrastructural development, all of them may have had the tendency not to converge (Abramovitz,1986), while it was possible that a subgroup of them may have been converging. This is because proximate countries are often in direct competition and can benefit from spillovers.

Further contributions of this study are: (1) it uses the dataset of World Development Indicators of the World Bank that covers more countries compared to the previous study by Beyzatlar and Yetkiner (2017); this is because the dataset of World Bank allows scholars to obtain more reliable, consistent and robust empirical results, inferences and conclusions. (2) We constructed transportation infrastructure by a composite index of transportation (CIT) which comprises air transport, freight (AIRT), roads total network kilometers (km) (RNWS), and rail lines (total route-kilometers (km)) (RALI) using principal component analysis (PCA).

Our findings suggest the presence of panel convergence at the global level, while the income groups exhibited panel divergence. However, we identified convergence clubs using an iterative testing procedure. The key findings from the club convergence algorithm results suggest that: (i) at the global level, club 1 converges; (ii) at income group levels the number of clubs formed differs and they exhibited divergence and convergence features. The rest of the paper is organised as follows: section 2 reviews the empirical literature. Section 3 presents the Phillips and Sul (2007, 2009) methodology alongside the data source. Section 4 presents the empirical results and discussion. Section 5 concludes with policy recommendations.

2. Literature review

The transportation literature has provided the role that transportation development/infrastructures play in stimulating/promoting productivity, growth and development in both developed and less developed countries/regions (inter alia: Gillen, 1996; Berechman, 2006; Weinert et al., 2007; Gunasekera et al., 2008; Hong et al., 2011; Yamamoto & Talvitie, 2011; Hof & van der Hoorn, 2012; Huzayyin & Salem, 2013; Pradhan & Bagchi, 2013; Deng, 2014; Laird & Mackie, 2014; Kim et al., 2017; Chakrabarti, 2018; Park et al., 2019; Tang & Abosedra, 2019; Wang & Wang, 2019; Zhang et al., 2019; Cong et al., 2020), with different methodologies, data sources, and different time periods either at country level or at the level of a panel of countries. Most studies have concluded that transport infrastructure can lead to productivity, growth, and the development of countries. For example, improved transport infrastructural development facilitates: economic growth; welfare by reducing the cost of accessing goods and services; encourages the mobility of the production factors via foreign direct investment; increasing the quality of travelling; strong influence on knowledge diffusion, technological spillover, and hence plays an important role in improving human capital formation through its effects on the idea of distance (Baier & Banister, 2012; Deng, 2013). There is clear comprehensive evidence in the direction that transportation measures have positive interaction with income dynamics. While there is much literature on the economic impact of transport infrastructure, the convergence in transportation infrastructures has suffered neglect. This is one of the reasons that this article examines the convergence in the transportation infrastructures at both global and income group levels with the available data from the World Bank database. To the best of our knowledge, the first study to investigate the convergence in transportation is the one conducted by Beyzatlar and Yetkiner (2017). Their study conjectures a transportation convergence equation and tested it via Difference GMM and System GMM methods, using 4-year span panel data from 15 European Union countries (EU-15) for the period 1970-2013. The results provide strong evidence for the existence of unconditional convergence among the EU-15 countries in two transportation measures, namely, inland freight transportation per capita, and inland passenger transportation per capita. The estimates show that the convergence is even stronger when control variables are used. They conclude that the previously found pattern of income convergence of EU-15 in the process of economic integration is also clearly seen in the transportation sector.

Since the inception of the seminal work on convergence of Solow (1956), Swan (1956), Barro (1991) and Barro and Sala-i-Martin (1992), many studies in the field of economics have explored the concept, but with one focusing on transportation (inter alia: De Bijl & Peitz, 2008; Liu, 2013; Xia, 2016; Saba & Ngepah, 2019a). It is on this basis that we are applying the concept of convergence to transportation infrastructures by using a different methodology. However, prior to this time, several studies have also applied the concept to transportation infrastructures for the purpose of drawing inferences and recommending policies. The study/concept on convergence began to gain prominence among scholars after the classical works of Solow (1956, 1957) and Swan (1956). Since then, the critical question that several papers have tried to address is whether there is a long-run tendency towards catching-up. This is a question that has taken the centre stage in every convergence discourse. After the Solow (1956, 1957) and Swan (1956) classical works, the concept of convergence was later further expanded by Barro and Sala-i-Martin (1991, 1992). They were the first set of scholars to introduce the concept of β and σ-convergence. The concept of β and σ-convergence has been used by several studies to investigate whether poorer countries/regions grow faster than richer countries, suggesting that they will catch up (β-convergence) in the long-run, or whether the dispersion of income diminishes (σ-convergence) over time.

The study of the concept of convergence has been understood in different ways by scholars, and these ways include: convergence within an economy vs. convergence across economies; convergence in terms of growth rate vs. convergence in terms of income level; unconditional (absolute) convergence vs. conditional convergence; global convergence vs. local or club-convergence; income-convergence vs. TFP (total factor productivity)-convergence; and deterministic convergence vs. stochastic convergence (Islam, 2003). Not all these different concepts of convergence were obvious from the outset, but research on convergence has proceeded through different stages. Convergence research has also witnessed the use of different methodologies, which may be classified broadly as follows: informal cross-sectional method; formal cross-sectional method; panel method; time-series method; and distribution approach (Islam 2003). For example, Phillips and Sul (2007) proposed a different approach for the discussion of convergence issues. The Phillips and Sul (2007, 2009) methodology is based on the structure of a 'non-linear, time-varying coefficients factor model'. Phillips and Sul (2007, 2009) argue that convergence may be an ongoing process because some countries may be catching-up without having reached the steady state. In such cases, a rejection of convergence would not be fair and that was why they proposed the concept of relative/club convergence, which considers the transition path of each country together with its growth performance to find convergence. Club convergence implies that a set of economies, countries, states and regions with similar conditions and structural characteristics (such as technology, preferences, political systems etc.) tend to converge to the same steady state, or economies with similar characteristics move from a disequilibrium position to their club-specific steady state positions (Phillips & Sul, 2007).

One of the empirical studies that have examined the convergence in transportation suggests the following: firstly, none of the foregoing studies has used the combined methodological approach proposed by Phillips and Sul (2007, 2009); secondly, the dataset of the World bank that spans 1990 to 2018 with 102 countries, has not been used to test the club convergence/divergence of global convergence in transportation by applying the Phillips and Sul (2007, 2009) methodology. Thirdly, the use of panel data for a longer period (here 29 years) is extremely important to establish the potential catch-up in transport infrastructure among the income group of countries. This is because it requires factors such as skills, high quality regulatory and business environments, and infrastructure availabilities - which usually could take time. Lastly, in the context of convergence, previous studies have not focused attention on countries when they are classified into four income groups. Hence, the rationale for this study.

3. Methodology and Data

In this section, the study discusses the different steps involved in executing the clustering algorithm that allowed for classifying countries into different income groups. The essence of this is to examine the panel and club convergence, alongside the panel transition curves.

3.1 Log t convergence test

Phillips and Sul (2007) propose log X_{it} which is decomposed into two parts: the common factor, μ_t, and the idiosyncratic factor loading δ_{it} that absorbs the error terms ε_{it}. Both the common factor (μ_t) and idiosyncratic factor loading (δ_{it}) are time-variant. The μ_t determines the common transportation infrastructures path according to the relation:

$$log\ X_{it} = \delta_{it}\mu_t \quad (1)$$

The above formulation enables the study to test whether the factor loading δ_{it} converges or otherwise. To accomplish this, Phillips and Sul (2007) constructed the panel relative transition coefficient/parameter, h_{it}, as:

$$h_{it} = \frac{log\ X_{it}}{\frac{1}{N}\sum_{i=1}^{N} logX_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N}\delta_{it}} \quad (2)$$

This helps in measuring the coefficient of factor loading δ_{it} in respect to the average panel series of the transition path for the economy i. The relative transition curves portray the relative transition coefficients h_{it}, estimated from equation (2). Convergence implies that an individual unit approaches the sample average over time. Therefore, the following holds:

(1) $\delta_{it} \rightarrow \delta\ for\ all\ i\ as\ t \rightarrow \infty\ implies\ that\ the\ transition\ coefficient\ \delta_{it}\ converges\ toward$

$\delta\ as\ t \rightarrow \infty$ (3)

(2) $h_{it} \rightarrow 1\ for\ all\ i\ as\ t \rightarrow$
$\infty\ implies\ that\ the\ equivalent\ to\ convergence\ of\ the\ relative\ transition$
$coefficient\ h_{it}\ toward\ unity\ as\ t \rightarrow \infty$ (4)
(3) $H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \rightarrow 0\ for\ all\ i\ as\ t \rightarrow \infty\ implies\ hat\ the\ cross -$
$sectional\ variance\ of\ h_{it}$,
$H_t, converges\ toward\ zero\ as\ t \rightarrow \infty$ (5)

From equations 3, 4 and 5, to account for possible nonstationary panel transition behaviour which may be caused by a decrease in the cross-sectional variance of a sample, even when there is no panel convergence and only local convergence within certain subgroups, Phillips and Sul (2007) proposes the following semiparametric specification of δ_{it}:

$$\delta_{it} = \delta_i + \propto_i \psi_{it} L(t)^{-1} t^{-\sigma} \quad (6)$$

where δ_{it} is the time-invariant part of the country-specific factor loading δ_{it}, *L(t)* is a slowly variant increasing function (with $L(t) \rightarrow \infty\ as\ t\ \rightarrow \infty$), σ is the decay rate (i.e. the speed of convergence), and ψ_{it} is a weakly autocorrelated random error variable (ψ_{it} is *iid*(0,1)). Based on the time-varying factor presentation in equation (1), Phillips and Sul proposed a convergence test and clustering algorithm based on the log t convergence test that is based on a simple time-series regression involving a one-sided t-test. In the framework, the null hypothesis is as follows:

H_0: Convergence for all i H_0: δ_i = δ and $\sigma\ \geq 0$ vs: H_1: No convergence for all i H_1: $\delta_i \neq$ δ and $\sigma < 0$ (7)

The testing procedure involves the following three steps:

1. To determine the cross-sectional variance ratio as captured by the ratio of hypotheses

H_1/H_t (from Equation 5).

2. Estimation of the following OLS regression:

$$\log\left(\frac{H_1}{H_t}\right) - 2logL(t) = \hat{a} + \hat{b}logt + \hat{\varepsilon_t}, for\ t = [gT], [gT] + 1, \ldots, T \quad for\ some\ g > 0 \quad (8)$$

3. One-side t test for $\sigma \geq$ using $\hat{b}(\hat{b} = 2\hat{\sigma})$ and HAC standard error. g ($g \in (0, 1)$) is a truncation parameter that shortens the regression by a certain fraction of the first observations. Monte Carlo simulations by Phillips and Sul (2007) suggest the use of g = 0.3 and *L(t)* = log t for samples up to T = 34. Given the assumptions outlined by Phillips and Sul (2007), the standard critical values can be applied such that the null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. The club clustering/convergence and Club merging algorithm framework can be found in the appendix of this study.

3.2 Club clustering/convergence and Club merging algorithm

The log t test is rejected for samples that do not converge overall. Phillips and Sul (2007) developed a club clustering algorithm to detect both convergence clubs and diverging regions, countries, or sectors. The algorithm consists of the following four steps:

Step 1 (Last Observation Ordering): We ordered the members of the panel according to the last observation, since evidence of convergence will, in general, be most apparent in the recent years. However, in the case of substantial time-series volatility in X_{it}, the ordering of the series can be done based on time-series averages of the final observations. In this study, the first approach was used.

Step 2 (Core Group Formation): We attempted to identify a core group of countries that provide strong evidence of convergence. Specifically, we estimated a sequence of $log\ t$ regression using the k highest members (Step 1) for all different values of k(i.e $2 \leq K < N$). We chose the regression that generates the maximum convergence t-statistic $t_{\hat{b},k}$ (where $t_{\hat{b},k} > -1.65$ so that convergence was ensured for the corresponding group). The corresponding group formed the core convergence group.

Step 3 (Club Membership): We then evaluated each individual country not included in the core convergence group (Step 2) for membership in this group. In more detail: we added one country at a time and calculated the convergence t-statistic from the $log\,t$ regression. The new country (member) satisfies the membership condition if the associated t-statistic is greater than a chosen critical value c^* (i.e $t_{\hat{b}} > c^*$). All countries that satisfy the membership condition were added to the core convergence group. Finally, we checked whether the whole group (i.e. the members of the initial core group and the additional selected members) satisfied the criterion for convergence.

Step 4 (Recursion and Stopping): We ran the log t regression for all the countries for which $t_{\hat{b}} < -1.65$ in the previous step. If the null hypothesis was not rejected, those countries formed a second convergence club. In case it was rejected, we repeated steps 1-3 on the remaining countries to determine whether the group itself could be subdivided into convergence clusters. If there was no k in step 2 for which $t_{\hat{b}} > -1.65$, we concluded that the remaining countries displayed divergent behaviour. The analysis of this study is further complemented with the application of the Phillips and Sul (2009) test of club merging in order to ensure the robustness of our results.

3.3 Club merging algorithm

Although the above procedure helps in identifying cluster formations of all possible configurations such as the panel convergence and divergence, converging subgroups, and single diverging units. This study still applied the Phillips and Sul (2009) methodology which helps in merging clubs when the procedure outlined above tends to overestimate the number of clubs above their true number. This is because Phillips and Sul (2007) recommend highly conservative values of the critical value c in step 3, in particular c = 0, in order to reduce the risk of including a false member into a convergence group. For this reason, Phillips and Sul (2009) propose convergence testing between convergence clubs as well. If the null is not rejected, the corresponding clubs can be merged into a larger club. For this purpose, we considered another formulation of the alternative hypothesis, apart from the one given in the above section (i.e. $H_A: \beta_i \neq \beta,\ \ or\ \alpha < 0$):

$$H_A: v_{\text{it}} \rightarrow \begin{cases} v_1 \\ v_2 \end{cases} and\ \alpha \geq 0\ \ if\ i\ \epsilon\ G_1, and\ \alpha \geq 0\ if\ \epsilon\ G_2 \tag{9}$$

Where the number of individual $G_1$and G_2 aggregates to *N.*

This can also be extended to the case of multiple clubs. The relative transition coefficient is then defined as:

$$h_{it} = \frac{v_{it}}{N^{-1}\sum_{i=1}^{N} v_{it}} \rightarrow \begin{cases} \frac{v_1}{\gamma v_1 + (1-\gamma) v_2} \\ \frac{b_2}{\gamma v_1 + (1-\gamma) v_2} \end{cases} i\ \epsilon\ G_1, i\ \epsilon\ G_2 \tag{10}$$

and:

$$H_t = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 \rightarrow \frac{\gamma(1-\gamma)\{\gamma v_1^2 + (1-\gamma) v_2^2\}}{\{\gamma v_1 + (1-\gamma) v_2\}^2} \quad (11)$$

For all $\gamma \neq 0, 1$ and $v_1 \neq v_2$, and we finally arrive at a *log t* regression model in the form of Equation 8. Applying the above procedure helped us to test the club convergence or divergence of transportation infrastructures.

3.4 Data and description

This study used annual data from 1990 to 2018 for the 102 countries, which were obtained from the World Development Indicators of the World Bank. The choice of the period and countries was due to the availability of data from the World Bank database. Countries are grouped based on different income levels to obtain different convergence results among different income groups (see Table 1). First, the 102 countries were classified into four income groups based on the World Bank classification of the world's economies into low (LIC), lower-middle (LMIC), upper-middle (UMIC), and high-income countries (HIC). We based this disaggregation on Gross National Income (GNI) per capita, calculated using the World Bank Atlas method[4]. The three indicators of transportation infrastructure (TRI) used for this study include: air transport, freight (AIRT);[5] roads total network (km) (RNWS);[6] and rail lines (total route-km) (RALI).[7] Rail lines (total route-km) (RALI) are the length of railway route available for train service, irrespective of the number of parallel tracks. air transport, freight (AIRT) is the volume of freight, express, and diplomats/diplomatic bags carried on each flight stage (operation of an aircraft from take off to its next landing). Roads total network (km) (RNWS) includes motorways highways and main or national roads secondary or regional roads and all other roads in a country. These three indicators are identified by the World Bank as transportation infrastructures (World Bank, 2021). The choice of the variables used to measure transport infrastructural endowment also follows previous studies of Wang et al. (2021), Pradhan (2019), Saidi et al. (2018), Farhadi (2015), Sutherland et al. (2009) and Irmen et al. (2009). Hence, the rationale behind our choice of these indicators for this study. Studies on transportation tend to evaluate the performance of the transportation infrastructure indices based on different indicators but this study follows the literature by using the three indicators mentioned above. Thus, this study measures transportation infrastructures by a composite index of transportation (CIT) which comprises air transport (AIRT); roads total network (km) (RNWS); and rail lines (total route-km) (RALI) to capture the activities of the transportation services as ensured by adequate infrastructures and infrastructure. The total population was used to transform the data because the comparison of different cross-sectional dimensions needs to be set at the same level, that is, into per capita units in order to avoid biased results. We used principal component analysis (PCA) to create these composite indices[8]. There were missing data, and this was taken care of through a projection by linear trend extrapolation of matching known data points by the least squares method, and moving the average interpolation procedure for missing data in between two data points[9].

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[4] See Table 1 for details on the classifications. The standard for grouping based on GNI per capita may have changed over some years, but very few countries have moved from one group to the other.
[5] WDI (2021). Available at: http://data.worldbank.org/indicator
[6] WDI (2021). Available at: http://www.econstats.com
[7] WDI (2021). Available at: http://data.worldbank.org/indicator
[8] Detailed descriptions of how to formulate these indices are available in Pradhan et al. (2018) and David (2019).
[9] Studies that have used these techniques include David (2019), Saba & Ngepah (2019b, 2019c), Saba & David (2020), Saba (2020a,b, c), Saba & Ngepah (2020).

Table 1: List of countries used in the estimations ranked by World Bank GNI per capita

Low income countries (LIC)	Lower-middle-income countries (LMIC)	Upper-middle-income countries (UMIC)	High-income countries (HIC)
Congo, Dem. Rep.	Algeria	Albania	Australia
Madagascar	Bangladesh	Armenia	Austria
Mali	Benin	Azerbaijan	Belgium
Mozambique	Cambodia	Belarus	Canada
Sudan	Cameroon	Bosnia and Herzegovina	Chile
Syrian Arab Republic	Congo, Rep.	Botswana	Croatia
Tajikistan	Cote d'Ivoire	Brazil	Czech Republic
Uganda	Egypt, Arab Rep.	Bulgaria	Denmark
	Eswatini	China	Estonia
	Ghana	Cuba	Finland
	India	Gabon	France
	Kenya	Georgia	Germany
	Kyrgyz Republic	Indonesia	Greece
	Mauritania	Iran, Islamic Rep.	Hungary
	Moldova	Iraq	Ireland
	Mongolia	Jordan	Israel
	Morocco	Kazakhstan	Italy
	Myanmar	Malaysia	Japan
	Nigeria	Montenegro	Korea, Rep.
	Pakistan	North Macedonia	Latvia
	Philippines	Peru	Lithuania
	Senegal	Russian Federation	Luxembourg
	Sri Lanka	Serbia	Netherlands
	Tanzania	South Africa	New Zealand
	Tunisia	Thailand	Norway
	Ukraine	Turkey	Poland
	Uzbekistan	Turkmenistan	Portugal
	Vietnam		Romania
	Zambia		Saudi Arabia
	Zimbabwe		Slovak Republic
			Slovenia
			Spain
			Sweden
			Switzerland
			United Kingdom
			United States
			Uruguay

4. Empirical results and discussion

4.1 Summary statistics, correlation matrix and principal component results analysis

Before going for a detailed examination, we quickly looked at the data of the composite index of transportation, their variation across income groups, hence summary statistics, and the results are reported in Table 2. In Panel A, the summary statistics for each of the variables under the full sample and the four income groups are presented. We observed that for the full sample, the mean (or median) value of air transport (AIRT), roads total network (km) (RNWS), and rail lines (total route-km) (RALI) is around 3.766 (or 3.672), 4.089 (or 4.248), 7.946 (or 7.876). The maximum and minimum values of the three variables are found to be approximately between 12.256 and -9.349, respectively. This implies that there is evidence of heterogeneity among the sample. Similarly, standard deviation (SD) is noticed around 3.126, 1.384, 1.365 for AIRT, RNWS and RALI, respectively, which indicate the variation in samples. The negative skewness for AIRT and RNWS shows a negatively skewed distribution for the two variables, while the positive skewness value for RALI shows the positively skewed distribution. To save space, a similar interpretation holds for the income groups. The Jarque-Bera statistics for the full sample and the four income groups with corresponding probability values of the normality test suggest that the residuals of the variables are not normally distributed, at least at the 10% significance level. Before starting the discussion of the convergence results, this study first constructed a composite index of transportation using a principal component analysis (PCA). The indices include three variables: air transport, freight (AIRT), roads total network (km) (RNWS), and rail lines (total route-km) (RALI). Panel B in Table 2 reports the correlation matrix for three variables, and shows that the variables are statistically significant. The correlation coefficients between these three variables are highly correlated. The high collinearity between the three variables helped us to construct the composite index of transportation using PCA. Table 3 presents the results of the PCA and the eigenvalues of all three components. PCA tries to cover maximum variance among the features in a dataset, it may in the process miss some information as compared to the original list of features. Therefore, to overcome this challenge, we carefully retain the component with an eigenvalue greater than one and eigenvectors those associated with variables whose loading exceeds 0.40 in absolute value (Chen, 2014). The composite index of transportation was constructed using the factor scores based on the eigenvalue of the first component. This study ignored the other two components because their eigenvalues were of less significance to the model. This was further supported by the scree plot graph[10].

Table 2: Summary statistics and correlation matrix results

Panel (A): Summary statistics										
Variables	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
Full sample										
AIRT	3.766	3.672	10.669	-9.349	3.126	-0.223	2.701	35.286	0.000	2958
RNWS	4.089	4.248	6.933	0.108	1.384	-0.332	3.072	54.818	0.000	2958
RALI	7.946	7.876	12.256	4.06	1.365	0.513	3.338	143.993	0.000	2958
LIC										
AIRT	2.623	2.323	9.627	-3.772	2.699	0.882	4.595	61.463	0.000	261
RNWS	3.797	3.699	5.297	2.344	0.733	0.133	2.354	5.306	0.070	261
RALI	7.378	7.543	10.316	5.557	0.959	-0.075	2.340	4.980	0.083	261
LMIC										
AIRT	2.735	2.776	7.902	-5.615	2.362	-0.371	2.772	21.841	0.000	870
RNWS	3.893	4.091	5.742	0.694	1.117	-0.632	2.931	58.112	0.000	870
RALI	7.559	7.513	11.134	5.298	1.152	0.943	4.280	188.327	0.000	870
UMIC										
AIRT	3.313	3.430	10.137	-9.350	3.381	-0.448	2.991	26.232	0.000	783
RNWS	3.768	3.819	6.933	0.166	1.542	-0.094	2.501	9.284	0.010	783
RALI	7.961	7.820	11.436	4.905	1.495	0.473	2.818	30.227	0.000	783
HIC										
AIRT	5.352	6.037	10.669	-5.809	3.034	-0.627	2.470	82.865	0.000	1073
RNWS	4.567	4.555	6.907	0.108	1.433	-0.711	3.736	114.635	0.000	1073
RALI	8.400	8.194	12.256	4.060	1.351	0.164	3.745	29.607	0.000	1073

Panel (B): Correlation matrix			
	AIRT	RNWS	RALI
AIRT	1.000		
RNWS	0.495***		
	(0.000)	1.000	
RALI	0.237***	0.311***	
	(0.000)	(0.000)	1.000

Note: *** denotes statistical significance at 1% level. p-value in parentheses. Air transport (AIRT); Roads total network (RNWS); and Rail lines (RALI). **Source**: **Author's computations.**

[10] This can be found in the appendix of this study.

Table 3: Principal component results

Panel (A): Principal component results				
Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	1.708	0.914	0.569	0.569
Component 2	0.795	0.298	0.265	0.834
Component 3	0.497	-	0.166	1.000
Panel (B): Principal components (eigenvectors) results				
Variable	Component 1	Component 2	Component 3	Unexplained
AIRT	0.605	-0.449	0.658	0
RNWS	0.634	-0.228	-0.738	0
RALI	0.481	0.864	0.147	0
Panel (C): Retained Principal Component results				
Variable	Component 1	Unexplained		
AIRT	0.605	0.375		
RNWS	0.634	0.312		
RALI	0.481	0.604		
Source: **Author's computations.**				

4.2 Convergence analysis

Table 4 reports the results of the panel and club convergence methodology composite index of transportation (a proxy for transportation infrastructures) for the world, and the four income groups. Under the world and income groupings, the first rows report the results of testing for full convergence, while other rows show the results of the club clustering procedure/algorithm and the final club merging results. We started by examining the world/full sample results before the income groups. Under the full sample for the world, the null hypothesis of full panel convergence for the transportation infrastructures is accepted (since the $t_{\hat{b}}$>-1.65, that is, 2.887>-1.65) indicating that they do converge to the same steady state. According to Phillips and Sul (2007), the sign of the point estimate is also a way of evaluating convergence patterns. Since $\hat{b} = 2\hat{\sigma} = \hat{\sigma} = \hat{b}/2 = 6.699/2$ is positive, the speed of adjustment implies strong convergence for the world over the full sample period. The club clustering algorithm results for the world is presented in Table 4. For club 1 under the world, the null hypothesis of club convergence is accepted (since $t_{\hat{b}}$= 2.887>-1.65). Since $\hat{b} = 2\hat{\sigma} = \hat{\sigma} = \hat{b}/2 = 6.699/2$, is positive, the speed of adjustment for club 1 implies strong convergence for the countries in club 1. There was no club merging algorithm result because the algorithm procedure provided one club. Figure 1 depicts the panel relative transition curves for the world/full sample, which was calculated from Equation 2. These curves show the behaviour/performance of the composite index of transportation for countries relative to the panel average. According to theory, under the assumption of convergence for the full panel of countries, the relative transition path tends to be in unity for all countries. On the other hand, under the assumption of club convergence (i.e., when groups of countries converge to different equilibria), the relative transition paths of the members of each club converge to different constants. A visual inspection of these curves enabled us to gain some insight into the outcomes of the testing methodology, and to monitor the transportation infrastructures course for each country relative to the sample average. In summary, a careful visual inspection of the panel transition paths for the world, over the period of the study, showed that these countries exhibited major divergence between the years 2004 and 2006. After the interval of these two years, the countries were seen to be converging again, even though they still exhibited minor decoupling before and after years between 2004 and 2006. Although the countries are at different levels of transport infrastructural development, the results from this study suggest that they are moving toward convergence, and the speed of convergence is strong. The full sample result for the world suggests evidence of a conditional/relative convergence[11] towards the average, as the value of the log t parameter is

[11] Note that conditional or relative convergence implies tending towards the sample average and a transition parameter equal to 1.

6.699. The countries in the full sample exhibited both transition paths above 1 and those below 1. This implies that world governments at one point or another appear to have chosen both similar and dissimilar paths for their transportation infrastructure/policy measures. Under the world results, the first club suggests evidence of conditional or relative convergence towards the panel average, as the value of their log *t* parameter is also 6.699. The findings from the full sample (world level) could not be compared with the one conducted by Beyzatlar and Yetkiner (2017) because it mainly focuses on EU-15 countries. One of the reasons that could be linked to the convergence of transportation infrastructures is that the global transportation industry has and it is still undergoing tremendous change due to privatisation and deregulation, evolving infrastructural capabilities and increased competition in the sector.

Under the full sample for low-income countries (LIC), the null hypothesis of full panel convergence for the transportation infrastructures was rejected (since the $t_{\hat{b}}$<-1.65, that is, -8.024<-1.65), indicating that they do not converge to the same steady state. According to Phillips and Sul (2007), the sign of the point estimate is also a way of evaluating convergence patterns. Since $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -0.281/2 is negative, the speed of adjustment implies weak convergence for LIC over the full sample period. The club clustering algorithm results show that the null hypothesis of club convergence is rejected for club 1. The sign of the point estimate is also a way of evaluating convergence patterns and the result shows that it is positive (since $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -0.281/2), which implies that the speed of adjustment for the club convergence is weak for LIC over the full sample period. Under the full sample for lower-middle-income countries (LMIC), the null hypothesis of full panel convergence for the transportation infrastructures was rejected (since the $t_{\hat{b}}$<-1.65, that is, -34.101<-1.65), indicating that they do not converge to the same steady state. This implies divergence of the LMIC. The point estimate result shows that the speed of adjustment implies weak divergence for LMIC over the full sample period, since $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -2.608/2 is negative. We ran the club merging algorithm test across the sub-clubs to avoid overestimation of the LMIC clubs. The results under LMIC show that clubs 2+3 cannot be merged (since the $t_{\hat{b}}$<-1.65, that is, -26.251<-1.65), while clubs 1+2 can be merged (since the $t_{\hat{b}}$>-1.65, that is, -0.698>-1.65). For LMIC, the results for the final club classifications show that the null hypothesis of club convergence is accepted for club 1 (since $t_{\hat{b}}$>-1.65, that is, -0.698>-1.65) which implies that the countries in this club are converging. While clubs 2 do not converge (since $t_{\hat{b}}$<-1.65, that is, -33.014<-1.65). The point estimate results for the clubs show that the speed of adjustment implies weak convergence for club 1 and weak divergence for club 2 for LMIC over the full sample period (since their $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -1.200/2 (club 1) and -2.747/2 (club 2) is negative).

Figures 2 (LIC) and 3 (LMIC) depicts the panel relative transition curves calculated from Equation 2. These curves show the behaviour of the composite index of transportation relative to the panel average for the LIC and LMIC. A visual inspection of these curves shows the composite index of transportation course for each country relative to the sample average. In summary, a careful visual inspection of the panel transition paths for the two income groups showed that these countries exhibited divergence (most especially the LMIC) and convergence at some point over the study period. The convergence club results for the composite index of transportation suggest that the countries in the income groups are at different levels of transport infrastructural development. The full sample for LIC and LMIC does not suggest evidence of conditional/relative convergence. This implies that there are no tendencies towards the sample average and a transition parameter equal to 1. This suggests that the LIC and LMIC are backward in transport infrastructural development and this calls for closing transport infrastructural development gaps among the countries in the income groups. The reasons for the absence of convergence may be due to low economic status, poor infrastructural development, high poverty and inequality, inefficient institutions etc.

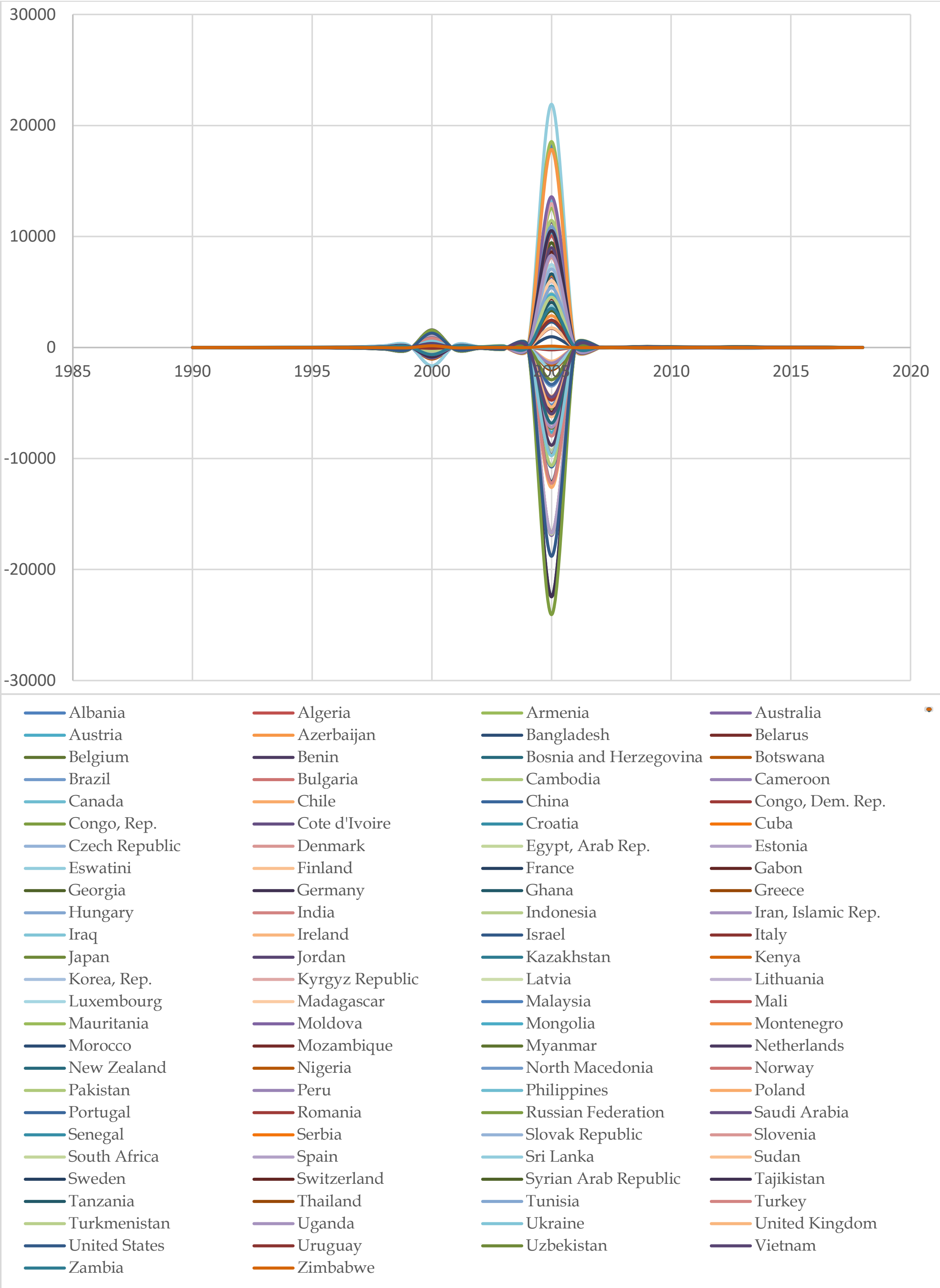

Figure 1. Transportation panel transition paths for the World countries/full sample

Under the full sample for upper-middle-income countries (UMIC), the null hypothesis of full panel convergence for the transportation infrastructures was rejected (since the $t_{\hat{b}}$<-1.65, that is, -6.731<-1.65), indicating that they do not converge to the same steady state. This implies divergence of the UMIC. The point estimate result shows that the speed of adjustment implies weak divergence for UMIC over the full sample period, since $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -6.386/2 is negative. We ran the club merging algorithm test across the sub-clubs to avoid overestimation of the UMIC clubs as suggested by Phillips and Sul (2009). The results under UMIC show that clubs 1+2 cannot be merged (since the $t_{\hat{b}}$<-1.65, that is, -29.813<-1.65), while clubs 2+3 can be merged (since the $t_{\hat{b}}$>-1.65, that is, 14.327>-1.65). For UMIC, the results for the final club classifications show that the null hypothesis of club convergence is rejected for club 1 (since $t_{\hat{b}}$<-1.65, that is, -29.813<-1.65) which implies that the countries in this club are diverging. While clubs 2 do converge (since $t_{\hat{b}}$>-1.65, that is, 14.327>-1.65). The point estimate results for the clubs show that the speed of adjustment implies weak divergence for club 1 and strong convergence for club 2 over the full sample period (since their $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -2.812/2 (club 1) and 3.982/2 (club 2) is negative and positive, respectively).

Under the full sample for high-income countries (HIC), the null hypothesis of full panel convergence for the transportation infrastructures was rejected (since the $t_{\hat{b}}$<-1.65, that is, -19.228<-1.65), indicating that they do not converge to the same steady state. The point estimate for the panel convergence result shows that it is negative (since $\hat{b} = 2\hat{\sigma}$ = $\hat{\sigma}$= $\hat{b}/2$ = -0.616/2), the speed of adjustment implies weak convergence for HIC over the full sample period. We ran the club merging algorithm across the sub-clubs to avoid overestimation of the clubs, as recommended by the Phillips and Sul (2009) methodology. The test of club merging results under HIC shows that clubs 1+2, 2+3, 3+4 and 4+5 cannot be merged (since the $t_{\hat{b}}$<-1.65, that is, -13.090<-1.65, -29.410<-1.65, -2.951<-1.65 and -144.647<-1.65). Therefore, we still maintain the initial club convergence results. The club clustering algorithm results show that the null hypothesis of club convergence is rejected for clubs 2 and 5 (since their $t_{\hat{b}}$<-1.65) respectively. While the null hypothesis of club convergence is accepted for clubs 1, 3 and 4 (since their $t_{\hat{b}}$ value is greater than >-1.65) respectively.

Figure 4 and Figure 5 depict the panel relative transition paths for the rest of the income groups (that is, UMIC and HIC) calculated from Equation 2. These curves show the behaviour of the transportation infrastructures for the UMIC and HIC relative to the panel average. A visual inspection of these curves enabled us to gain some insight into the outcomes of the testing methodology and to monitor the transportation infrastructure course for each income group relative to the sample average. In summary, an inspection of the transition curves for the two income groups shows that countries exhibited both divergence and convergence patterns at some point over the study period. Although the decoupling/ coupling of the curves is more evident in UMIC. The panel transition curves tend to support the clustering algorithm results, which makes the findings of this study valid for the income groups under study.

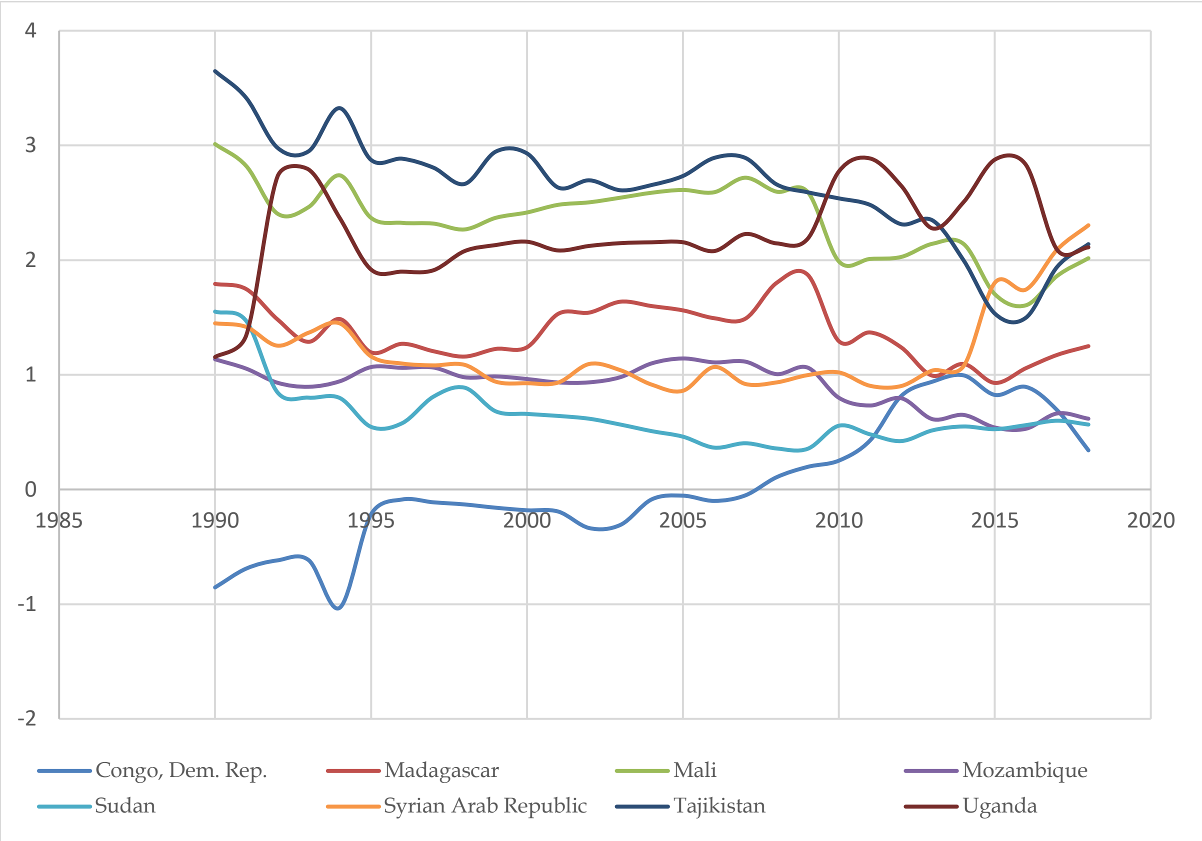

Figure 2. Transportation panel transition paths for Low-income countries (LIC)

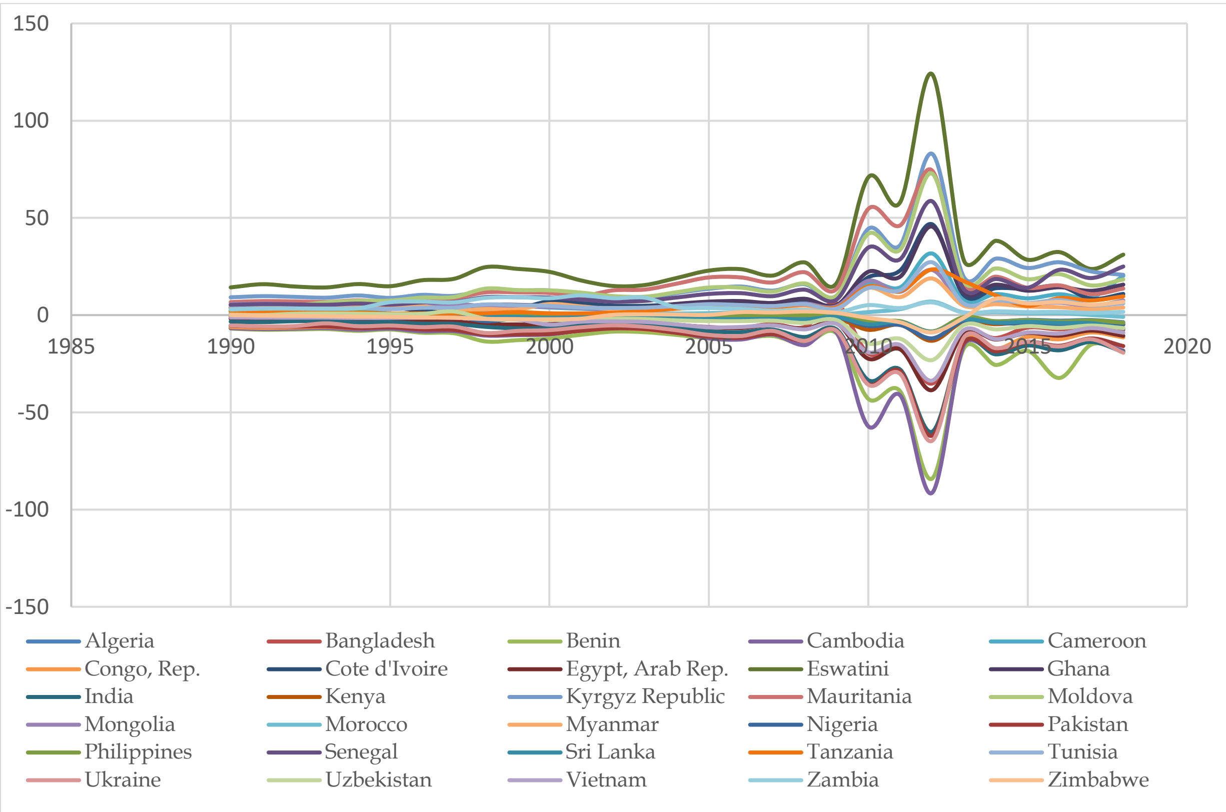

Figure 3. Transportation panel transition paths for Lower-middle-income countries (LMIC)

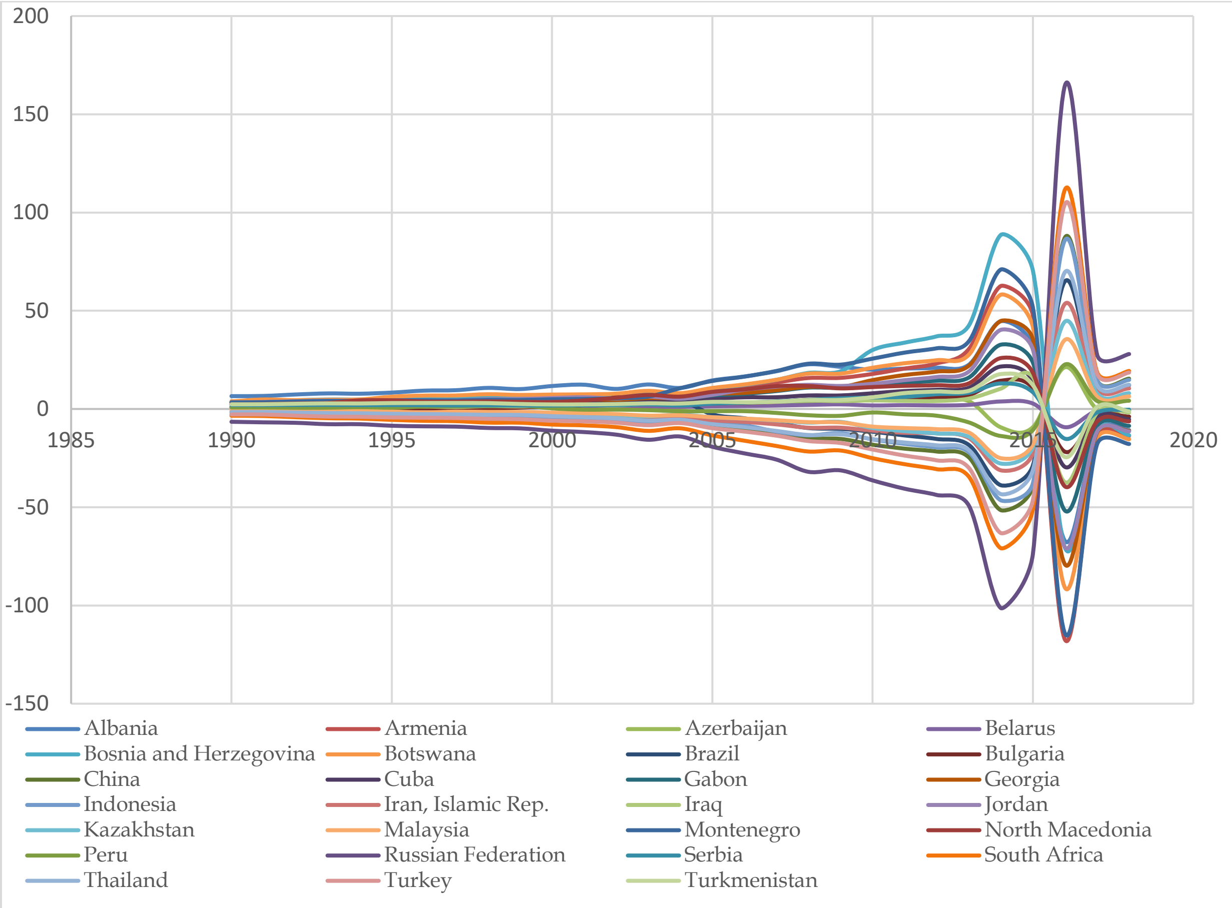

Figure 4. Transportation panel transition paths for Upper-middle-income countries (UMIC)

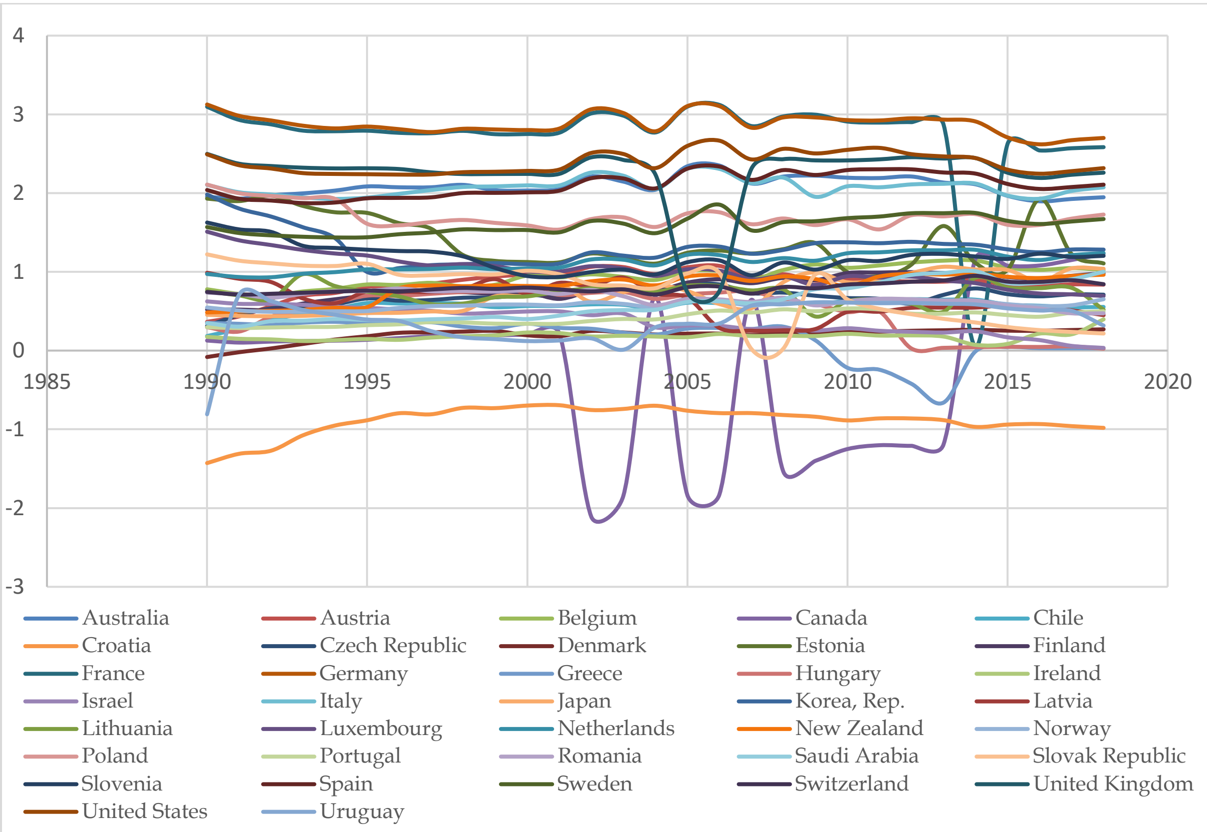

Figure 5. Transportation panel transition paths for High income countries (HIC)

Table 4: Transportation and final club convergence results (club merging) for the world and four income groups

Sample	Countries	$\hat{b}\ Coeff$	SE	$t-Stat$
World Level				
Full sample		6.699	2.320	2.887
First Club	| Albania | Algeria | Armenia | Australia | Austria | Azerbaijan | Bangladesh | Belarus | Belgium | Benin | Bosnia and Herzegovina | Botswana | Brazil | Bulgaria | Cambodia | Cameroon | Canada | Chile | China | Congo, Dem. Rep. | Congo, Rep. | Cote d'Ivoire | Croatia | Cuba | Czech Republic | Denmark | Egypt, Arab Rep. | Estonia | Eswatini | Finland | France | Gabon | Georgia | Germany | Ghana | Greece | Hungary | India | Indonesia | Iran, Islamic Rep. | Iraq | Ireland | Israel | Italy | Japan | Jordan | Kazakhstan | Kenya | Korea, Rep. | Kyrgyz Republic | Latvia | Lithuania | Luxembourg | Madagascar | Malaysia | Mali | Mauritania | Moldova | Mongolia | Montenegro | Morocco | Mozambique | Myanmar | Netherlands | New Zealand | Nigeria | North Macedonia | Norway | Pakistan | Peru | Philippines | Poland | Portugal | Romania | Russian Federation | Saudi Arabia | Senegal | Serbia | Slovak Republic | Slovenia | South Africa | Spain | Sri Lanka | Sudan | Sweden | Switzerland | Syrian Arab Republic | Tajikistan | Tanzania | Thailand | Tunisia | Turkey | Turkmenistan | Uganda | Ukraine | United Kingdom | United States | Uruguay | Uzbekistan | Vietnam | Zambia | Zimbabwe |	6.699	2.320	2.887
Income Groupings				
Low-income countries (LIC)				
Full sample		-0.281*	0.035	-8.024
First Club	|Congo, Dem. Rep. Madagascar | Mali | Mozambique| Sudan | Syrian Arab Republic | Tajikistan | Uganda	-0.281*	0.035	-8.024
Lower-middle-income countries (LMIC)				
Full sample		-2.608*	0.077	-34.101
First Club	Congo, Rep. | Egypt, Arab Rep. | Eswatini |	-1.512*	0.066	-22.803
Second Club	| Algeria | Bangladesh | Benin | Cameroon | Cote d'Ivoire |	-2.425*	0.075	-32.464
Third Club	Cambodia | Ghana | India | Kenya | Kyrgyz Republic | Mauritania | Moldova | Mongolia | Morocco | Myanmar | Nigeria | Pakistan | Philippines | Senegal | Sri Lanka | Tanzania | Tunisia | Ukraine | Uzbekistan | Vietnam | Zambia | Zimbabwe	-2.747*	0.083	-33.014
Test of Club merging				
Club 1+2		-1.200	1.718	-0.698
Club 2+3		-2.984**	0.114	-26.251
Final club classifications				
First Club	| Algeria | Bangladesh | Benin | Cameroon | Congo, Rep. | | Cote d'Ivoire | Egypt, Arab Rep. | Eswatini |	-1.200	1.718	-0.698
Second Club	|Cambodia | Ghana | India | Kenya | Kyrgyz Republic| Mauritania | Moldova | Mongolia | Morocco | Myanmar | Nigeria | Pakistan | Philippines | Senegal | Sri Lanka	-2.747*	0.083	-33.014

	| Tanzania | Tunisia | Ukraine | Uzbekistan | Vietnam | Zambia | Zimbabwe			
Upper-middle-income countries (UMIC)				
Full sample		-6.386*	0.949	-6.731
First Club	| Albania | Armenia | Belarus | Bosnia and Herzegovina | Brazil | Bulgaria | China | Cuba |	-3.193*	0.112	-28.444
Second Club	| Azerbaijan | Botswana |	-1.725*	0.065	-26.543
Third Club	| Gabon | Georgia | Indonesia | Iran, Islamic Rep. | Iraq | Jordan| Kazakhstan | Malaysia | Montenegro | North Macedonia | Peru | Russian Federation | Serbia | South Africa | Thailand | Turkey |Turkmenistan |	0.904*	0.023	39.555
Test of Club merging				
Club 1+2		-2.812**	0.094	-29.813
Club 2+3		3.982	0.278	14.327
Final club classifications				
First Club	| Albania | Armenia | Belarus | Bosnia and Herzegovina | Brazil | Bulgaria | China | Cuba |	-2.812*	0.094	-29.813
Second Club	| Azerbaijan | Botswana | Gabon | Georgia | Indonesia | Iran, Islamic Rep. | Iraq | Jordan| Kazakhstan | Malaysia | Montenegro | North Macedonia | Peru | Russian Federation | Serbia | South Africa | Thailand | Turkey |Turkmenistan |	3.982	0.278	14.327
High-income countries (HIC)				
Full sample		-0.616*	0.032	-19.228
First Club	| Australia | Canada | Chile | Croatia | Denmark | Greece |	0.047	0.199	0.235
Second Club	| Belgium | France | Germany | Hungary |	-1.197*	0.041	-29.002
Third Club	| Austria | Czech Republic |	0.353	0.111	3.169
Fourth	| Estonia | Finland |	1.006	0.092	10.989
Fifth	| Ireland | Israel | Italy | Japan | Korea, Rep. | Latvia |Lithuania | Luxembourg | Netherlands | New Zealand | Norway | Poland | Portugal | Romania | Saudi Arabia | Slovak Republic | Slovenia | Spain | Sweden | Switzerland | United Kingdom | United States | Uruguay |	-0.774*	0.004	-191.691
Test of Club merging				
Club 1+2		-0.633**	0.048	-13.090
Club 2+3		-1.004**	0.034	-29.410
Club 3+4		-0.487**	0.165	-2.951
Club 4+5		-0.747**	0.005	-144.647

Note: *,** indicates rejection of the null hypothesis of convergence and club convergence merging at the 5%, respectively. SE is the standard error.

The study findings at the global level reflected normal maturation of the transport industry of countries, while previously less developed countries approached the early adopters of new transport infrastructure over time. Given that the global level data comprises both the developed and less developed countries, it seems possible that initially, less developed and less efficient/capable countries in terms of their transport infrastructure provision have been catching up with the more developed and more efficient/ capable countries through the spread of new transport infrastructures and know-how between countries of the world. The convergence at the global level could also reflect an increasing awareness of the importance of the transportation sector for the socio-economic development of countries in the world. The findings of this study suggest that countries are gradually becoming more homogeneous at a relatively fast speed, with regard to the air transport (AIRT), roads network (RNWS), and rail lines (RALI) of their transportation infrastructures, even though there is still a lot to be accomplished. The results also suggest that some countries in the income groups in one way or another have developed their transportation infrastructures to the extent that they are catching up with countries that have more advanced transportation infrastructures.

To conclude this section, this study found that the speed of panel convergence differs among the income groups and in this regard, we must mention that variation in the speed of convergence among different income groups must have contributed to the overall convergence at the full sample level. However, this may depend on the gap between the income groups, the relative positions of the income groups, and their respective speed of convergence. Finally, although our empirical findings at the global and income group levels suggest the presence of panel convergence and panel divergence in transportation, respectively, it did not allow us to identify the underlying reasons for this convergence/divergence. In particular, we do not know which driving forces led some countries/income group of countries to develop and upgrade their transportation infrastructures substantially faster, to catch up with others in the composite index under study. The study by Schuckmann et al. (2012) presented relevant trends and driving forces (e.g. digitalisation, mobility, urbanisation), or external and internal drivers (e.g. technological development, social development, fuel development, transport impact on environment) that may determine the development of transport infrastructure which are not explicitly examined in this study in relation to how they contribute to convergence or divergence of the countries. Therefore, the distinguishing characteristics behind this catching up in the transportation infrastructures/sector of the countries remain unclear. Nor could the study explicitly identify the role of transport policy and regulation in the transportation sector of the countries in the index patterns regarding the development of transportation infrastructures. These are major issues for further research across the income groups.

5. Conclusion and policy recommendations

The issue of convergence in transportation has not attracted much interest among researchers, and this study, therefore, contributes to the existing literature by examining the convergence in transport infrastructure at the global level for 102 countries for the period 1990-2018. To investigate the important issue of whether one size does in fact fit all regarding transportation convergence, we classified our panel data into four income groups based on the World Bank classification of the world's economies into low (LIC), lower-middle (LMIC), upper-middle (UMIC), and high-income countries (HIC). We based this disaggregation on Gross National Income (GNI) per capita, calculated using the World Bank Atlas method[12]. This is because according to Barro (1990), the different levels of countries' incomes may also determine their convergence/divergence.

The main findings of this study suggest the presence of panel convergence at the global/full sample and panel divergence in the income group. However, we identified convergence clubs using an iterative testing procedure, but the club convergence results could not be generalised across the income groups as there were both convergent and divergent clubs. The convergence and non-convergence of the full sample and the presence of the different subgroup convergence clubs for the composite index of transportation imply that the income groups and countries at large are characterised by individual factors, which in turn determine an idiosyncratic course of their own path for transportation policies. Since the world level result (that is, panel convergence) in this study comprises of both the transport poor and transport rich countries, the findings of this study

[12] See Table 1 for details on the classifications. The standard for grouping based on GNI per capita may have changed over some years, but very few countries have moved from one group to the other.

show that transport poor countries are catching up with the transport rich countries. By implication, this would possibly have enabled the transport poor countries not to pay the cost that is usually associated with initial learning, experimentation and evaluation of transportation infrastructures. Therefore, transport rich countries at the world level can further aid or support the catching-up of transport poor countries by formulating, implementing, coordinating and evaluating policies that will enable transport poor countries to move directly from the old to the new transportation infrastructures. This is because it may have the tendency to free the transport poor countries of the burden involving investment sunk in the old transportation infrastructures.

Finally, for policy direction, this study recommends that: (i) since factors affecting transportation infrastructures in income groups may differ, policymakers should identify and prioritise idiosyncratic income group-specific factors that are peculiar to the divergent income groups, and then decisively address them; (ii) transportation infrastructural gaps that may exist between countries and income groups need to be reduced by fostering transportation infrastructural cooperation for the purpose of making technological transfer and training in the transport sector easy; (iii) policies that would further enhance improvement in air transport (AIRT), road networks (RNWS), and rail lines (RALI) should be given priority across the four income groups; (iv) the governments in each of the income groups where the results suggest divergence in transportation should jointly formulate, implement, monitor, evaluate and review policies that would further enhance efficient operation of the transportation sector/services, for the purpose of achieving and maintaining convergence; (v) the information on emerging decoupling/coupling curves derived from transition paths could help policymakers exploit new opportunities, avoid threats, plan future R&D, and forecast technological trends in the transformation of the transport industry for countries and income groups. Since transportation infrastructures could drive economic, social and political development across the globe, there is a need to align different countries' income group and national transportation plans, policy guidelines and regulatory frameworks to the devolution realities, and to address key challenges that may hinder the transport sector from playing its rightful role in global national development. Given that this study suggests panel convergence of transportation infrastructures at the global level, the caveat is that world governments and policymakers should avoid policies that could bring about a widening in the gap of transportation infrastructures among countries and in the income groups.

Clearly, the results reported in this study should be treated as further findings on international convergence in transportation. Further research could apply the ESTAR nonlinear unit root/co-integration techniques to each of the transportation infrastructures used in this study, or even more indicators to examine whether they are converging/diverging. Furthermore, compared to this present study and previous studies, future research should use a dataset that is wider in scope in terms of time and number of countries by considering the determinants of club convergence of the transportation infrastructures. Investigating this would show researchers and policymakers factors responsible for the divergent and convergent income groups.

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