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Granger-causality between transportation and GDP: A panel data approach

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ABSTRACT

This paper investigates the Granger-causality relationship between income and transportation of EU-15 countries using a panel data set covering the period 1970–2008. In the study, inland freight transportation per capita in ton-km (TRP), inland passenger transportation per capita in passenger-km (PAS), and road sector gasoline fuel consumption per capita in kg of oil equivalent (GAS) are used as transportation proxies and GDP per capita is used as measure of income. Our findings indicate that the dominant type of Granger-causality is bidirectional. Instances of one-way or no Granger-causality were found to correspond with countries with the lowest income per capita ranks in 1970 and/or in 2008. Although we conclude that there is an endogenous relationship between income and transportation, this is not observed until after an economy has completed its transition in terms of economic development.

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1. Introduction

We are in the age of mobility, in which not only physical goods but also human beings and even services move between locations in significant amounts. The facilities that collectively make this unprecedented mobility possible are known as transportation. A natural question that follows this observation is whether transportation enhances economic development and growth, or vice versa, or whether they boost each other. On the one hand, economic intuition suggests that transportation may have strong positive effects on economic development and growth, which we will call in this study *direct causation*.[1] Three possible channels that transportation may affect economic development positively are as follows. Firstly, improvements and developments in transportation (e.g., faster trains and oil tankers with more capacity) and facilities improve overall productivity of production units (Bougheas et al., 2000; Lakshmanan, 2007). Secondly, increasing transportation eases technology spillovers across economies. Finally, a micro-level feature with potential macro-level results is rising profitability due to reduced costs or increasing sales revenue. This occurs because transportation and its facilities allow firms to access the lowest cost inputs or factors of production for their production activities, and to access broader markets and perhaps at potentially more advantageous prices.

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[1] Most of the studies in the literature refer to the effect of transportation on economic development as *direct causation* and the effect of economic development on transportation as *reverse causation*, as we do in this study.

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There is an enormous literature on the positive role of transportation on income. One branch of the literature considers infrastructure as an argument in production, which may be labeled as "the production function approach".[2] For example, Munnell and Cook (1990), investigating the impact of highways on Gross State Product (GSP), show that the elasticity of GSP with respect to highways is 0.06. Duffy-Deno and Eberts (1991), Eisner (1991), Garcia-Mila and McGuire (1992) and Moonmaw et al. (1995) similarly obtain positive relationships between transport infrastructure and income per capita by using production function approach. Jones (1990) and Mofidi and Stone (1990) show that highway spending per capita has positive impact on various measures of development, whereas Reynolds and Maki (1990) fail to find it. While Easterly and Rebelo (1993) find that public investment in transportation and communication (T&C) leads to higher economic growth in developing countries, Devarajan et al. (1996) find that there is a negative correlation between the two for 43 developing countries between 1970 and 1990. Boopen (2006) shows that, in Africa, investment in transportation capital is more productive than physical capital (investment) on average. Zhou et al. (2007) show that highway construction has significant and positive effect on economic growth in China. Singletary et al. (1995), Crihfield and Panggabean (1995), Garcia-Mila et al. (1996) and Fernald (1999) all show that increases in resources allocated to highways cause employment in the manufacturing industry to rise, leading to productivity growth. In a similar manner, Jiwattanakulpaisarn et al. (2010) found that investments in highways are likely determinants of state-level employment growth in the services sector.

Another branch of research, again investigating the relationship between transport measures and economic development, show that transport measures have cost reducing effects, therefore it may be called the "cost function approach". Berndt and Hansson (1992), Lynde and Richmond (1993), Seitz (1993), Nadiri and Mamuneas (1994), Conrad and Seitz (1994) and Boarnet (1996, 1998) may be considered in this vein. For example, Bougheas et al. (2000) introduce (transportation) infrastructure as a cost reducing technology in their cross-country study and find that improvements in the transportation infrastructure allow specialization and long run growth. They also show that, a cost reducing technology in infrastructure makes production of intermediate inputs more efficient compared to its impact on the efficiency in production of final goods.

On the other hand, the growing income, essentially due to technological progress, allows general demand to rise and leads to the development of the services sector (e.g., Eichengreen and Gupta, 2013). As transportation is an important component of services sector, intuition suggests that economic development may also have strong positive effects on transportation, which in this study we refer to as *reverse causation*. For example, Kim (2002), examining the determinants of optimal demand for transportation infrastructure using a recursive computable general equilibrium model, finds that higher levels of transportation capital stock are associated with higher economic growth and inflation. Specifically, he finds that a 1% increase in GDP generates 0.99% capital formation in transportation sector. Similarly, Randolph et al. (1996) find that per capita government expenditures on T&C increase with GDP per capita, among other indicators using pooled cross-sectional and time series data on 27 low and middle income economies between 1980 and 1986.

All these studies clearly indicate a potentially strong relationship between economic development and transportation, perhaps in both directions. It is important to determine the direction of relationship between income and transportation for both econometric and economic reasons. First, in terms of econometrics, if this relationship is in fact bidirectional, then studies undertaking one-way relationship between transportation and income involve a misspecification problem, that is, they will produce biased and inconsistent estimates of the structural parameters given the endogenous relationship between income and transportation. Second, in terms of economics, policy makers need to know the direction of relationship to be able to apply effective policies. For example, if policy makers wait for a rise in income to boost transportation, when in fact the direction of causality is from transportation to income for economies below a certain level of economic development, both income and transportation will develop at a lower rate compared to a case in which transportation is strongly supported, e.g., through subsidization. Hence, it is critical to determine the direction of the causality between transportation and economic development (GDP per capita level) in advance. Applying the Granger-causality (or rather Granger non-causality) test is the most effective and practical way to test the direction of causality (e.g., Florens and Mouchart, 1982). The essence of determining the relationship between income and transportation for reasons explained above serving as our motivation.

This paper aims to investigate the direction of causation in the Granger sense between income and transportation for the EU-15 countries by using a panel data set covering the period 1970–2008. Rather than taking transportation as a physical stock or public investment in infrastructure, we define transportation to mean all the facilities that make physical goods, human beings and services move between locations. To this end, inland freight transportation per capita in ton-km (TRP) and GDP per capita are used as measures of transportation and income, respectively. In addition to this, inland passenger transportation per capita in passenger-km (PAS) and road sector gasoline fuel consumption per capita in kg of oil equivalent (GAS) are used as transportation proxies in robustness tests.[3]

[2] By definition, infrastructure entails transportation. Hence, studies on the role of public capital or infrastructure on economic development and growth may also be considered relevant for this approach. Aschauer (1989) is the pioneering study, which shows that the elasticity of private sector productivity with respect to public capital is positive, which is also confirmed by Munnell (1990). Some examples of more recent studies of this approach are Bucci and Del Bo (2009) showing a U-shaped relationship between public capital share and economic growth for 184 countries in the period 1970–2004, and Carboni and Medda (2011) showing that core infrastructure (roads, highways, telecommunication systems, R&D capital stock) leads to different growth rates depending on their elasticity. See survey studies such as Button (1998) and Romp and de Haan (2007) for extensive discussion of the literature on the relationship between infrastructure and/or public capital and income or economic growth.

[3] For example, Lu et al. (2010), Meersman and Van de Voorde (2013), Santanu and Samyadip (2012) and Xiong and Sun (2010) use freight transportation; Owen and Phillips (1987) use passenger transportation; Pradhan and Bagchi (2013) use both freight and passenger transportation; Liddle (2009, 2012) use gasoline consumption as transportation proxies to examine the interaction with economic activities such as GDP.

Following Erdil and Yetkiner (2009), this study employs Granger non-causality test for heterogeneous panel data models, which can accommodate both dimensions of heterogeneity in this context, that of the causal relationships, and that of the data generating process (Hurlin, 2004a). To the best of our knowledge, the few studies that employ Granger causality test to analyze the direction of the relationship between transportation and economic growth undertake different approaches and show conflicting evidence. While some use panel data to test for causality, others use time series data for various countries. Furthermore, the transportation and economic growth variables used vary from study to study. For transportation, variables range from public investment in T&C, road and highway infrastructure to air passenger traffic as a proxy for public investment/capital spending. For economic growth, variables range from GDP, agricultural productivity growth to state-level employment. Haque and Kim (2003) and Bose and Haque (2005) both examine the relationship between public investment in T&C and economic growth by applying Granger-causality test using panel data for different sets of developing countries for the period 1970–1987. However, there are striking contrasts between findings of these two studies. Whereas the former finds that the growth in public investment in T&C Granger causes GDP for the 15 developing countries in their dataset, the latter finds that the causality runs from GDP growth to public investment in T&C sector for a panel of 32 developing countries. Both find causality in one direction only, i.e., neither finds causality in the opposite direction.

The causality between investment in T&C and economic development is also examined via time series data. Groote et al. (1999) conducts Granger-causality test in a multi-equation vector autoregressive (VAR) model for the Netherlands in the 1853–1913 period, finding that infrastructure investment in T&C positively causes GDP, but also that GDP negatively affects investment in T&C. Another study, Fedderke et al. (2006), examining the same relationship in South Africa for 1853–2001, similarly finds bidirectional causality between different definitions of economic infrastructure, one of which is T&C, and economic growth, but use a co-integration analysis, as opposed to a Granger-causality framework. Liddle (2009) shows that there is Granger-causality between gasoline consumption and gasoline price, between car ownership and income, and between car ownership and gasoline consumption in US for 1946–2006 using a Vector Error Correction Model (VECM) specification. Pradhan and Bagchi (2013) examine the effect of transportation infrastructure on economic growth in India for 1970–2010. Using VECM, they find bidirectional causality between road transportation, for which road length is taken as a proxy, and GDP growth. In addition they find unidirectional causality from rail transportation (for which rail length is taken as a proxy) and GDP growth. Cullison (1993) examines the effects of government investment in both physical and human capital on economic growth. Using a VAR model, he undertakes Granger-causality tests to determine the correlation between 21 different types of government spending and economic growth in the US Making use of data for 1955–1992, he finds no causality from transportation spending including railways, air, and highways to economic growth. In contrast, another study on the US by Kollias and Paleologou (2013) finds bidirectional causality between highway expenditures and GDP growth for the period 1956–2004 as a result of the nonlinear Granger-causality test they utilize.

Yet there are other studies pointing to unidirectional causality between further disaggregated variables of transportation and different measures of economic growth. Zhang and Fan (2004) conduct a Granger-causality test in a general method of moments (GMM) framework to study the relationship between road density and agricultural productivity growth of 290 districts in rural India in 1971–1994. They find a unidirectional causality from the former to the latter. Likewise, Jiwattanakulpaisarn et al. (2009), employing the same methodology for 48 states in the US, arrives at a similar conclusion that there is unidirectional causality running from highway infrastructure investment to private sector employment. Chen and Haynes (2012) also confirm unidirectional causality from surface transportation infrastructures (highway, rail and transit stock) to personal income and employment, but not in the opposite direction. In contrast, Fernandes and Pacheco (2010) determine unidirectional Granger-causality from GDP to demand for domestic air transport in Brazil between 1966 and 2006.

The hitherto evidence indeed puts forth mixed results for the causality between transportation and economic growth, pointing to a need for more detailed research. In this study, we therefore employ a larger data set and more refined technical analysis to verify the direction of the Granger-causality between transportation and GDP. We aim to supply more substantial evidence on the endogeneity of transportation and GDP by employing a panel data set Granger-causality test for EU-15 countries between 1970 and 2008. The reason for the selection of these countries for this specific time period is their status as high income economies with well-structured transportation sectors, thus providing a stable basis on which to analyze and identify the main factors of the issue at hand. We find that bidirectional Granger-causality is the leading type of causality for the sample countries. Instances of one-way or no Granger-causality were mainly found to correspond with countries with the lowest per capita ranks in 1970 and/or 2008, including Portugal, Greece and Italy. On this basis, we argue that bidirectional Granger-causality between income and transportation is observed only after an economy has completed its transition in terms of economic development, and further speculate that not all EU-15 economies have yet completed their transition to a steady state.

The organization of the paper is as follows. Section 2 summarizes the methodology of Granger non-causality test for heterogeneous panel data models, presents the test results including the robustness tests, showing that bidirectional Granger-causality is the leading type of causality for our sample of 15 countries. Section 3 is reserved for the conclusion.

2. A panel data approach

2.1. The methodology[4]

There are various approaches to running Granger (1969) causality tests in panel data models. In this study, we employ the approach proposed by Hurlin and Venet (2001), Hurlin (2004a, 2004b) and Hansen and Rand (2006), which treat the autoregressive coefficients and regression coefficient slopes as constants. As the methodology is discussed in detail by Erdil and Yetkiner (2009), we will present here a parsimonious summary. Let us consider two covariance stationary variables, x and y, observed on T periods and on N cross-section units. Granger (1969) causality is defined as follows: the variable $x_{i,t}$ causes $y_{i,t}$, if we are better able to predict $y_{i,t}$ by using all available information, compared to the use of information without $x_{i,t}$, for each individual $i \in [1, N]$. We will assume that the Granger-causality model is a linear one and therefore, we will study a time-stationary VAR representation, used for a panel data set. For each cross-section unit i and time period t, we estimate the following model:

$$y_{i,t} = \sum_{k=1}^{p} \beta_k y_{i,t-k} + \sum_{k=0}^{p} \theta_k x_{i,t-k} + u_{i,t} \tag{1}$$

where u is normally distributed with $u_{i,t} = \alpha_i + \varepsilon_{i,t}$, p is the number of lags, and $\varepsilon_{i,t}$ are *i.i.d.* $(0, \sigma^2)$. It is assumed that the autoregressive coefficients β_k and the regression coefficients θ_k's are constant for $k \in [1, N]$. Moreover, it is further assumed that the parameters β_k are identical for all individual countries, while the coefficients θ_k could have country-specific dimensions. In other words, the model utilized in this study is a panel data model with fixed coefficients (i.e., fixed effects model). The major attraction of fixed effects model is the ability to control for stable characteristics of the countries in the study, thereby eliminating potentially large sources of bias and satisfy the homogeneity through the observed countries. We used Hausman test, the correlated random effects test, and found that the fixed effects model is indeed the most appropriate specification. In addition, the similarity between these 15 EU member countries, all OECD members, also supports our specification qualitatively. Finally, the residuals are assumed to satisfy the standard properties, i.e., they are independently, identically, and normally distributed, and free from heteroskedasticity and autocorrelation.

In testing causality with panel data, it is important to pay attention to the question of heterogeneity between cross-section units. The first source of heterogeneity is caused by permanent cross-sectional disparities. A pooled estimation without the heterogeneous intercepts could lead to bias in the slope estimates, resulting in a fallacious inference in causality tests (Hurlin, 2004a). Another basis of heterogeneity is caused by heterogeneous regression coefficients, θ_k. In sum, the analysis of causality for panel data sets should consider the different sources of heterogeneity of the data-generating process. Thus, there are different types of causality hypothesis to be tested in a panel data set framework. These are summarized in Table 1.

The first test procedure, named as the Homogenous and Instantaneous Non-causality Hypothesis (HINC), is directed towards testing whether or not the θ_k's of $x_{i,t-k}$ are simultaneously null for all individual i and all lag k. For testing Np linear restrictions in HINC, the respective Wald statistics (F_{HINC}) is used. Since the individual effects, α_i, are assumed to be fixed, SSR_u and SSR_r are SSR obtained from the maximum likelihood (ML) estimation, which, in this case, corresponds to the fixed effects (FE) estimator.

If the HINC hypothesis is rejected, there are two possibilities. The first one is the Homogenous Causality Hypothesis (HC) and takes place if all the coefficients θ_k are identical for all lag k and are statistically different from zero. In other words, the aim is to test whether θ_k's in (1) are equal. As in the case of HINC, since country fixed effects, α_i, are assumed to be fixed, the ML estimator is consistent with the FE estimator.

If the HC hypothesis is also rejected, this means that the process is non-homogenous and no homogenous causality relationships can be obtained (Hurlin, 2004a). Nonetheless, such a situation need not entail the complete absence of any causality relationships between the two variables. It may still be possible that for one or more cross-section units, there exist causality relationships. Hence, the variable x causes the variable y for a single country or for a subgroup of cross-section units. In this study, however, no subgroups are examined. The final step is to test the Heterogeneous Non-Causality Hypothesis (HENC). In this case, the nullity of all the coefficients of the lagged explanatory variable $x_{i,t-k}$ is tested for each cross-section unit. These N individual tests identify the cross-section unit for which there are no causality relationships. If the HENC hypothesis is failed to reject, this means that there exists a single country for which the variable x does not cause the variable y.

2.2. The data and the model

The data is taken from the OECD Stat Extracts Database[5] for 15 EU member countries between 1970 and 2008 in order to test the direction of causality between real GDP per capita[6] (GDP) and transportation for which inland freight transportation per capita in ton-km (TRP) is taken as a proxy, in a panel data setting. The following two models are estimated:

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[4] This sub-section heavily draws from Erdil and Yetkiner (2009).

[5] http://stats.oecd.org/Index.aspx.

[6] US $, constant prices, constant PPP, base year 2005.

Table 1
Types of causality tested in a panel data framework.[a]

Name	Hypothesis tested	Test statistic
Homogenous and Instantaneous Non-Causality Hypothesis (**HINC**)	$H_0: \ \theta_k = 0 \quad \forall\ i \in [1,N], \forall k \in [0,p], i \neq j$ $H_1: \ \theta_k \neq 0 \exists (i,k)$	$F_{HINC} = \frac{(SSR_r - SSR_u)/(Np)}{SSR_u/[NT - N(1+p) - p]}$
Homogenous Causality Hypothesis (**HC**)	$H_0: \ \theta_k^i = \theta_k^j \quad \forall\ i,j \in [1,N], \forall k \in [0,p]$ $H_1: \ \theta_k^i \neq \theta_k^j \exists (i,j,k)$	$F_{HC} = \frac{(SSR'_r - SSR_u)/[p(N-1)]}{SSR_u/[NT - N(1+p) - p]}$
Heterogeneous Non-Causality Hypothesis (**HENC**)	$H_0: \ \theta_k^i = 0 \quad \forall\ i \in [1,N], \forall k \in [0,p]$ $H_1: \ \theta_k^i \neq 0 \quad \forall\ i \in [1,N], \forall k \in [0,p]$	$F_{HENC} = \frac{(SSR''_r - SSR_u)/p}{SSR_u/[NT - N(1+2p) + p]}$

Note: SSR_u stands for the sum of squared residuals unrestricted and SSR_r stands for the sum of squared residuals restricted for the respective H_0.
[a] Please refer to Erdil and Yetkiner (2009) for details.

Table 2
Descriptive statistics for GDP and TRP (1970–2008).

	GDP (US$, 2005 prices)	TRP (ton-km)
Mean	23,847	3479
Median	22,235	3330
Maximum	74,021	8494
Minimum	8502	83
Observations	585	585

Table 3
Panel co-integration test results.

Pedroni panel co-integration test			
Null hypothesis: no co-integration			
Individual	Panel rho-statistic	−3.687***	Co-integration relationship is found
	Panel PP-statistic	−3.997***	
	Panel ADF-statistic	−2.683***	
Common	Panel rho-statistic	−2.638***	
	Panel PP-statistic	−3.566***	
	Panel ADF-statistic	−3.828***	
Kao panel co-integration test result			
Null hypothesis: no co-integration			
ADF	*t*-Statistic	2.912***	Co-integration relationship is found
Johansen Fisher Panel Co-integration Test			
Null hypothesis	Fisher statistic (trace test)	Fisher statistic (max-Eigen test)	Co-integration relationship is found
None	91.50***	90.62***	
At most 1 co-integration relation	32.29	32.29	

*** Reject H_0 at 1% level of significance.

$$\Delta GDP_{i,t} = \sum_{k=1}^{p} \beta_k \Delta GDP_{i,t-k} + \sum_{k=0}^{p} \theta_k \Delta TRP_{i,t-k} + u_{i,t} \tag{2}$$

$$\Delta TRP_{i,t} = \sum_{k=1}^{p} \beta_k \Delta TRP_{i,t-k} + \sum_{k=0}^{p} \theta_k \Delta GDP_{i,t-k} + v_{i,t} \tag{3}$$

For both variables, we take the natural logarithms. We further difference the data in order to eliminate possible unit roots.[7]

2.3. Descriptive statistics and panel co-integration analysis

As an initial step before the causality procedure, descriptive statistics for the common pooled data are given in Table 2, and for each individual country in Appendix A in Tables A1a and A1b.

[7] Indeed, we found that the original series of GDP and TRP contain unit root. According to Hadri and Breitung, panel unit root tests series are found to be integrated of order 1. Breitung tests the existence of unit root as the null hypothesis. The test statistics of both series show that we cannot reject the null hypothesis. Hadri tests the stationarity of series as the null hypothesis. Test statistics lead us to reject at 1% significance level.

Table 4
Number of lags for GDP and TRP.

Variable	Lag1	Lag2	Lag3	Number of lags
GDP	−1.223	−1.393	−1.376	2
TRP	−4.535	−4.683	−4.670	2

Table 5
Hausman test (correlated random effects) for cross-section.

Test statistic	GDP to TRP	TRP to GDP	Hausman test
Chi-Sq. statistic	13.367**	11.562**	No random effect

*** Reject H_0 at 1% level of significance.
** Reject H_0 at 5% level of significance.

Table 6
Test results for homogeneous causality hypotheses.

Country group	Test	Causality from GDP to TRP	Causality from TRP to GDP
EU-15	HINC	162.436***	6.723***
	HC	126.747***	9.081***

*** Reject H_0 at 1% level of significance.

We can see that real GDP per capita ranges from a minimum of 8502 to a maximum of 74,021 dollars, and that the average GDP per capita is 23,847 dollars. The inland freight volumes range from 83 to 8494 ton-km per capita and that the average inland freight transportation is 3479 ton-km. Next, panel co-integration analyses are applied to non-stationary variables, using three different panel co-integration tests, to examine whether there is a possible co-integration relationship between GDP and TRP. The results are given in Table 3.

Although all panel co-integration tests have different methodologies, Table 3 clearly shows that there is panel co-integration relationship between GDP and TRP for the period 1970–2008. This finding also justifies our main aim, which is to analyze the direction of the relationship between these two variables via Granger-causality tests.

2.4. Bidirectional causality between transportation and income: pooled estimation

As a first step to exploring the causality between transportation and income, the lag lengths were chosen for both variables. Table 4 presents Akaike Information Criterion (AIC) figures for each variable. Consequently, we choose two lags for both GDP and TRP.

Second, Hausman Test is performed to determine whether fixed effects or random effects model is the preferred model specification. The test is applied for both directions, namely GDP to TRP and TRP to GDP. The values of Hausman Test from Table 5 show that the random effects specification is rejected. Consequently, the fixed effects specification is used for unbiased and consistent estimation.[8]

After choosing the lag lengths and confirming fixed effects model, Eqs. (2) and (3) were estimated for each country group in order to test HINC and HC hypotheses. Table 6 demonstrates the values of Wald statistics for testing the non-causality (HINC) and homogenous causality (HC) hypotheses.[9] Rejecting the null hypothesis of HINC at 1% level of significance shows the existence of a causality relation between GDP and TRP. The next question is whether the causality is an overall (homogenous) causality for each country group, or originates from causality relations for individual countries (heterogeneous). The null hypothesis of HC is also rejected at 1% level of significance, which indicates the nonexistence of a homogenous causality between GDP and TRP.

The next step in the search for causality is to reveal individual countries' contribution to the existence of causality. For this purpose, we estimate Eqs. (2) and (3), in which θ_k's differ among countries in our data set and HENC hypothesis is tested for each individual country. The results of F_{HENC} test (given in the last row of Table 1) are presented in Table 7.

According to Table 7, bidirectional causality relation is observed for 8 of 15 countries, meaning that for approximately 53%, causality is both from GDP to TRP and TRP to GDP. The results, however, become more interesting if we order countries according to their GDP per capita. We first list them with respect to their income per capita in 1970 in Appendix A in Table A2. Countries ranked in this way reveal a clear pattern: those ranked as high income countries in 1970 can be seen to have either bidirectional causality or causality running from GDP to TRP (the first nine countries). On the other hand, those at the lower end evidently either have no causality in Granger sense (e.g., Greece) or mixed results (some have causality running from TRP to GDP and some the other way around). Heuristically speaking, we conjecture that bidirectional

[8] For detailed information see Hausman (1978) and Hausman and Taylor (1981).
[9] Please refer to rows 1 and 2 for HINC and HC hypotheses in Table 1.

Table 7
Test results for heterogeneous causality hypothesis.

Country	Test	Causality from GDP to TRP	Causality from TRP to GDP
Austria	HENC	3.565**	2.369*
Belgium	HENC	7.996***	6.354***
Denmark	HENC	4.875***	2.131
Finland	HENC	6.627***	3.765**
France	HENC	4.127**	3.256**
Germany	HENC	15.783***	7.593***
Greece	HENC	1.625	1.766
Ireland	HENC	1.177	2.974**
Italy	HENC	1.612	2.607*
Luxembourg	HENC	4.475***	5.973***
Netherlands	HENC	7.726***	9.524***
Portugal	HENC	0.853	12.139***
Spain	HENC	10.946***	1.494
Sweden	HENC	2.426*	0.958
United Kingdom	HENC	5.925***	6.658***

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Granger-causality between income and transportation is observed after a certain level of development is achieved. In contrast, mixed results are observed in those countries in which transition is incomplete. We also ranked the list of countries according to their 2008 income in Appendix A in Table A3. Our interpretation does not change in the sense that while higher income countries have a strong tendency to show bidirectional Granger-causality between income and transportation or causality from GDP to transportation (reverse causality), lower income countries have an equally strong tendency to show either no Granger-causality, or Granger-causality running from transportation to GDP.

2.5. Robustness tests

In the previous section the bidirectional causality between TRP and GDP was examined and heterogeneous causality was found for 15 OECD member EU countries for the period 1970–2008. In this section, we undertake a robustness check of our results by repeating our analysis with different transportation variables. In particular, inland freight transportation per capita (TRP) is replaced with inland passenger transportation per capita in passenger-km (PAS) and road sector gasoline fuel consumption per capita in kg of oil equivalent (GAS) as alternative proxies for transportation, respectively compiled from OECD Stat Extracts Database[10] and the World Bank[11] for the same 15 EU member countries.

The first step is the determination of the lag lengths. Table 8 presents Akaike Information Criterion (AIC) results for each variable: we choose two lags for GDP–PAS and three lags for GDP–GAS.

In the second step, we undertake the Hausman test to determine whether fixed effects or random effects model is the preferred model specification in our analyses. Hausman test is applied for road sector gasoline fuel consumption per capita and inland freight transportation per capita for both directions, namely GDP to GAS and GAS to GDP, and GDP to PAS and PAS to GDP, respectively. Table 9 shows that the random effects specification is rejected at 1% significance level. Therefore, the fixed effects specification is used for the analysis of freight transportation and gasoline consumption relationships with GDP.

In the third step, after choosing the lag lengths and undertaking the Hausman test, Eqs. (2) and (3) are estimated for each country group in order to test HINC and HC hypotheses. Table 10 demonstrates the values of Wald statistics for testing two types of homogenous causality hypothesis.[12]

The test results show no evidence of causality between GDP and PAS with respect to HINC hypothesis. Two sources might be giving rise to this outcome. First of all, since PAS includes only rail and road (passenger cars, buses or coaches) transport modes leaving out airline transportation; it may not able to reflect the actual passenger transportation, though transportation by passenger cars account for the highest percentage of inland passenger transportation in EU-15 countries.[13] Second, the recent decoupling trend between PAS and GDP, GDP growth outpacing inland passenger transportation growth, especially since 2000s, may be the reason for the nonexistence of causality between the two.[14] On the other hand, we find evidence of

[10] http://stats.oecd.org/Index.aspx.
[11] http://databank.worldbank.org/data/views/reports/tableview.aspx.
[12] Please refer to rows 1 and 2 in Table 1.
[13] For instance, the percentage of transportation by passenger cars in inland passenger transportation range from minimum 72.8% in Greece to maximum 93.4% in Luxembourg in 2000, and from minimum 78.2% in Austria to maximum to 87.4% in the UK in 2010. See, http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Passenger_transport_statistics, Fig. 1.
[14] See, for example, Tapio (2005) for a detailed discussion of decoupling, and Fig. 2 in http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Passenger_transport_statistics which shows that GDP grew faster than the level of inland passenger transportation in 12 of the EU-15 countries between 2000 and 2010.

Table 8
Number of lags for GDP–PAS and GDP–GAS.

Variable	Lag1	Lag2	Lag3	Lag 4	Number of lags
GDP-PAS	−4.929	−5.107	−5.103		2
GDP-GAS	−8.049	−8.246	−8.250	−8.203	3

Table 9
Hausman test (correlated random effects) for cross-section.

Test statistic	GDP to GAS	GAS to GDP	Hausman test
Chi-Sq. statistic	14.423**	43.747***	No Random Effect
Test statistic	GDP to PAS	PAS to GDP	Hausman test
Chi-Sq. statistic	60.557***	47.431***	No random effect

** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Table 10
Test results for homogeneous causality hypotheses.

Country group	Test	Causality from GDP to PAS	Causality from PAS to GDP
EU-15	HINC	0.561	0.909
	HC	–	–
	Test	Causality from GDP to GAS	Causality from GAS to GDP
	HINC	2.749**	6.652***
	HC	3.284**	8.614***

** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Table 11
Test results for heterogeneous causality hypothesis.

Country	Test	Causality from GDP to GAS	Causality from GAS to GDP
Austria	HENC	0.991	0.878
Belgium	HENC	0.771	3.994**
Denmark	HENC	1.922	5.596***
Finland	HENC	1.865	1.934
France	HENC	2.302*	6.188***
Germany	HENC	3.171**	4.627***
Greece	HENC	7.655***	4.409***
Ireland	HENC	1.769	2.184*
Italy	HENC	0.598	3.751**
Luxembourg	HENC	2.214*	1.667
Netherlands	HENC	1.149	2.634**
Portugal	HENC	2.747**	2.504*
Spain	HENC	10.816***	1.297
Sweden	HENC	0.586	0.948
United Kingdom	HENC	3.274**	1.105

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

causality between GDP and GAS, as we reject both of the null hypotheses of HINC at 1% and 5% levels of significance. The next question is whether the causality between GAS and GDP is an overall (homogenous-HC) causality for each country group, or originates from causality relations for individual countries (heterogeneous-HENC). Our analysis supports the existence of heterogeneous causality, similar to GDP versus TRP, as the HC hypothesis is rejected. Hence, the causality originates from causality relations for individual countries.

Table 12
The comparison of HENC results between GDP–TRP and GDP–GAS.

Country	Test	GDP–TRP	GDP–GAS
Austria	HENC	bidirectional	no causality
Belgium	HENC	*bidirectional*	*one-way*
Denmark	HENC	**one-way**	**one-way**
Finland	HENC	bidirectional	no causality
France	HENC	**bidirectional**	**bidirectional**
Germany	HENC	**bidirectional**	**bidirectional**
Greece	HENC	no causality	bidirectional
Ireland	HENC	**one-way**	**one-way**
Italy	HENC	**one-way**	**one-way**
Luxembourg	HENC	*bidirectional*	*one-way*
Netherlands	HENC	*bidirectional*	*one-way*
Portugal	HENC	*one-way*	*bidirectional*
Spain	HENC	**one-way**	**one-way**
Sweden	HENC	one-way	no causality
United Kingdom	HENC	*bidirectional*	*one-way*

The fourth step is to test the individual countries' contribution to the existence of heterogeneous causality. For this purpose, we estimate Eqs. (2) and (3) where θ_k's differ among countries in our data set and HENC hypothesis is tested for each individual country between GDP and GAS. The results of F_{HENC} test (cf. the last row of Table 1) are presented at Table 10.

According to Table 11, bidirectional causality relation is observed for only 4 countries (France, Germany, Greece and Portugal), and no causality relation is observed for 3 countries (Austria, Finland and Sweden) among the 15 countries in our dataset. Moreover, one-way causality relation is observed for 8 countries: from GAS to GDP for 5 (Belgium, Denmark, Ireland, Italy and the Netherlands), and in the opposite direction for 3 (Luxemburg, Spain and the UK). The decrease in number of countries having bidirectional Granger-causality is perhaps due to the restrictive nature of GAS in reflecting the scope of transportation in an economy. It nonetheless shows that there is some Granger-causality (whether one-way or bidirectional) for 80% of sample countries.

Table 12 summarizes the results of our Granger-causality analysis for GDP–TRP and GDP–GAS (cf., Tables 7 and 11). Our comparison shows that TRP and GAS show identical Granger-causality results for 6 of the 15 countries. Variations in the results are expected since road sector gasoline fuel consumption per capita in kg of oil equivalent (GAS) has a limited capability to reflect the extent of transportation in an economy. However, we propose that the fact that 6 of 15 countries (40%) have identical results shows a degree of robustness for our Granger-causality results. As a final note, we would like to highlight the fact that Greece is distinctive in having bidirectional causality between GDP and GAS, despite the absence of any indication of causality between GDP and TRP. This is perhaps due to the significant role of road-based transportation in Greece.

We also order countries according to their real GDP per capita in 1970 and 2008 in Appendix A, in Tables A4 and A5, respectively. There is weak consistency in terms of Granger-causality among those ranked as high income, middle-income, and low-income countries for both base years. There appears to be a similar trend for middle and low-income ranked countries to show either bidirectional or one-way causality, whereas high-income countries show either one-way or no causality. One-way causality relationship is mostly direct causality from transportation to income both for high-income and low-income countries.

3. Concluding remarks

In this paper, we applied the Granger-causality approach to a panel data model with fixed coefficients in order to determine the direction of causality between GDP and inland freight transportation per capita (TRP). Although we found significant evidence of bidirectional causality, this causality is not homogenous. The tests for heterogeneous causality demonstrate that the leading type of causality is bidirectional. We also observe that both for 1970 and 2008, only relatively well developed economies clearly show bidirectional causality, while the majority of others show mixed results. All in all, our results point to a linkage between the level of development and transportation. We conjecture, therefore, that not all EU-15 countries have completed their transition to their long run level of development. In order to test the robustness of the model, we repeated the same Granger-causality analyses with both inland passenger transportation per capita (PAS) and road sector gasoline fuel consumption per capita (GAS) for the same countries and period, but this analysis failed to support any Granger-causality between PAS and GDP. The analysis shows that Homogenous and Instantaneous Non-Causality Hypothesis (HINC) and Homogeneous Causality Hypothesis (HC) are rejected, and that Heterogeneous Non-Causality Hypothesis (HENC) is observed between GDP and GAS. We find that our causality analysis between GAS and GDP supports the results of TRP and GDP only to a limited extent, due to the limited capability of GAS to reflect the true role of transportation in an economy. We argue that the determination of a link between rank of level of development and the nature of Granger-causality may have an important policy implication for those countries yet to complete their transition. The strong tendency to show either no Granger-causality, or Granger-causality running from transportation to GDP indicates the potentially important role of transportation in stimulating these economies.

Appendix A

See Tables A1a–A5.

Table A1a
Country-based descriptive statistics for GDP (1970–2008).

Country	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Obs.
Austria	25001.478	24564.543	36191.670	14692.820	6166.096	0.175	−1.075	39
Belgium	24409.324	24405.707	33593.778	15241.473	5412.805	0.129	−1.145	39
Denmark	25496.718	25080.389	34595.286	17307.429	5395.395	0.146	−1.274	39
Finland	21727.150	21054.042	33500.763	12786.702	5775.771	0.453	−0.659	39
France	23916.488	24423.756	31472.108	15341.731	4702.322	−0.032	−1.096	39
Germany	24714.270	24801.768	33828.873	15706.699	5336.814	−0.051	−1.250	39
Greece	18113.483	17177.263	26386.811	11922.900	3541.710	0.935	0.425	39
Ireland	20607.552	16227.377	41168.873	9218.392	10595.649	0.791	−0.912	39
Italy	22225.152	23288.316	29007.909	13584.036	4956.249	−0.234	−1.284	39
Luxembourg	42708.995	41060.489	74021.457	22970.730	16431.610	0.468	−1.177	39
Netherlands	26511.850	25395.010	38105.952	17777.968	6020.085	0.420	−1.117	39
Portugal	15500.401	15528.682	22067.972	8502.324	4451.879	0.147	−1.494	39
Spain	19535.588	19085.038	28527.092	11917.266	5057.302	0.410	−1.150	39
Sweden	24204.313	23697.667	34782.178	17329.775	5050.613	0.637	−0.580	39
United Kingdom	23044.602	22328.301	35093.963	14816.806	6217.053	0.538	−0.950	39

Table A1b
Country based descriptive statistics for TRP (1970–2008).

Country	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Obs.
Austria	4885.490	3687.087	8494.866	2363.037	2157.169	0.647	−1.404	39
Belgium	4620.026	4505.672	6820.043	2890.255	1325.414	0.198	−1.569	39
Denmark	2592.449	2569.895	3367.175	1676.694	529.461	−0.007	−1.103	39
Finland	6150.065	6207.773	8131.716	4053.139	1148.500	−0.100	−0.870	39
France	3805.477	3703.534	4577.381	3097.916	480.685	0.203	−1.382	39
Germany	4115.119	3622.062	6546.952	2648.978	1211.506	0.499	−1.052	39
Greece	1235.262	1232.308	1625.515	869.802	193.560	−0.056	−0.641	39
Ireland	1863.697	1622.946	4436.390	176.200	1373.811	0.549	−0.693	39
Italy	2937.134	3242.198	4077.275	510.815	844.253	−1.013	0.398	39
Luxembourg	3293.469	3280.979	4044.501	2539.620	344.243	−0.129	−0.221	39
Netherlands	4534.837	4417.311	5536.849	3821.433	548.870	0.582	−1.132	39
Portugal	969.052	1176.912	1975.804	82.917	733.511	−0.179	−1.706	39
Spain	3505.041	3157.173	6215.142	1864.938	1167.202	1.032	0.071	39
Sweden	5056.736	5032.711	6600.802	2786.467	809.303	−0.207	0.265	39
United Kingdom	2627.899	2661.989	3450.787	1991.185	483.951	0.145	−1.570	39

Table A2
Test results for heterogeneous causality hypotheses (ranked by 1970 real GDP per capita).

Rank in 1970	Country	Real GDP per capita (1970)	Causality from GDP to TRP	Causality from TRP to GDP
1	Luxembourg	5505	4.475***	5.973***
2	Sweden	4586	2.426*	0.958
3	Denmark	4218	4.875***	2.131
4	Netherlands	4015	7.726***	9.524***
5	Belgium	3832	7.996***	6.354***
6	Austria	3809	3.565**	2.369*
7	Germany	3775	15.783***	7.593***
8	France	3577	4.127**	3.256**
9	United Kingdom	3568	5.925***	6.658***
10	Italy	3387	1.612	2.607*
11	Finland	3335	6.627***	3.765**
12	Greece	2913	1.625	1.766
13	Spain	2686	10.946***	1.494
14	Ireland	2292	1.177	2.974**
15	Portugal	1864	0.853	12.139***

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Table A3
Test results for heterogeneous causality hypotheses (ranked by 2008 real GDP per capita).

Rank in 1970	Rank in 2008	Country	Real GDP per capita (2008)	Causality from GDP to TRP	Causality from TRP to GDP
1	1	Luxembourg	84,713	4.475^{***}	5.973^{***}
14	2	Ireland	41,493	1.177	2.974^{**}
4	3	Netherlands	41,063	7.726^{***}	9.524^{***}
6	4	Austria	37,858	3.565^{**}	2.369^{*}
3	5	Denmark	36,808	4.875^{***}	2.131
2	6	Sweden	36,790	2.426^{*}	0.958
11	7	Finland	35,918	6.627^{***}	3.765^{**}
9	8	United Kingdom	35,631	5.925^{***}	6.658^{***}
7	9	Germany	35,432	15.783^{***}	7.593^{***}
5	10	Belgium	35,288	7.996^{***}	6.354^{***}
8	11	France	33,090	4.127^{**}	3.256^{**}
13	12	Spain	31,455	10.946^{***}	1.494
10	13	Italy	31,253	1.612	2.607^{*}
12	14	Greece	28,896	1.625	1.766
15	15	Portugal	23,283	0.853	12.139^{***}

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Table A4
Test results for heterogeneous causality hypotheses (ranked by 1970 real GDP per capita).

Rank in 1970	Country	Real GDP per capita (1970)	Causality from GDP to GAS	Causality from GAS to GDP
1	Luxembourg	5505	2.214^{*}	1.667
2	Sweden	4586	0.586	0.948
3	Denmark	4218	1.922	5.596^{***}
4	Netherlands	4015	1.149	2.634^{**}
5	Belgium	3832	0.771	3.994^{**}
6	Austria	3809	0.991	0.878
7	Germany	3775	3.171^{**}	4.627^{***}
8	France	3577	2.302^{*}	6.188^{***}
9	United Kingdom	3568	3.274^{**}	1.105
10	Italy	3387	0.598	3.751^{**}
11	Finland	3335	1.865	1.934
12	Greece	2913	7.655^{***}	4.409^{***}
13	Spain	2686	10.816^{***}	1.297
14	Ireland	2292	1.769	2.184^{*}
15	Portugal	1864	2.747^{**}	2.504^{*}

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

Table A5
Test results for heterogeneous causality hypotheses (ranked by 2008 real GDP per capita).

Rank in 1970	Rank in 2008	Country	Real GDP per capita (2008)	Causality from GDP to GAS	Causality from GAS to GDP
1	1	Luxembourg	84713	2.214^{*}	1.667
14	2	Ireland	41493	1.769	2.184^{*}
4	3	Netherlands	41063	1.149	2.634^{**}
6	4	Austria	37858	0.991	0.878
3	5	Denmark	36808	1.922	5.596^{***}
2	6	Sweden	36790	0.586	0.948
11	7	Finland	35918	1.865	1.934
9	8	United Kingdom	35631	3.274^{**}	1.105
7	9	Germany	35432	3.171^{**}	4.627^{***}
5	10	Belgium	35288	0.771	3.994^{**}
8	11	France	33090	2.302^{*}	6.188^{***}
13	12	Spain	31455	10.816^{***}	1.297
10	13	Italy	31253	0.598	3.751^{**}
12	14	Greece	28896	7.655^{***}	4.409^{***}
15	15	Portugal	23283	2.747^{**}	2.504^{*}

* Reject H_0 at 10% level of significance.
** Reject H_0 at 5% level of significance.
*** Reject H_0 at 1% level of significance.

References

Aschauer, D.A., 1989. Is public expenditure productive? J. Monetary Econ. 23 (2), 177–200.
Berndt, E.R., Hansson, B., 1992. Measuring the contribution of public infrastructure capital in Sweden. Scand. J. Econ. 94 (Suppl. 1992), 151–168.
Boarnet, M.G., 1996. The Direct and Indirect Economic Effects of Transportation Infrastructure. University of California Transportation Center, Berkeley, Working Paper No. 340.
Boarnet, M.G., 1998. Spillovers and locational effects of public infrastructure. J. Reg. Sci. 38 (3), 381–400.
Boopen, S., 2006. Transport infrastructure and economic growth: evidence from Africa using dynamic panel estimates. Empirical Econ. Lett. 5 (1), 37–52.
Bose, N., Haque, M.E., 2005. Causality between public investment in transport and communication and economic growth. J. Econ. Develop. 30 (1), 95–106.
Bougheas, S., Demetriades, P.O., Mamuneas, T.P., 2000. Infrastructure, specialization, and economic growth. Canadian J. Econ./Revue Canadienned' Economique 33 (2), 506–522.
Bucci, A., Del Bo, C., 2009. On the Interaction between Public Investment and Private Capital in Economic Growth. University of Milan, Working Paper No. 2009–44.
Button, K., 1998. Infrastructure investment, endogenous growth and economic convergence. Ann. Reg. Sci. 32 (1), 145–162.
Carboni, O.A., Medda, G., 2011. Government spending and growth in a neoclassical model. Math. Financ. Econ. 4, 269–285.
Chen, Z., Haynes, K.E., 2012. Re-examining Linkages between Surface Transportation Infrastructure and Economic Performance: A Panel Granger Causality Test on the Northeast Corridor. George Mason University School of Public Policy Research Paper No. 2013-02.
Conrad, K., Seitz, H., 1994. The economic benefits of public infrastructure. Appl. Econ. 26 (4), 303–311.
Crihfield, J.B., Panggabean, M.P.H., 1995. Is public infrastructure productive? A metropolitan perspective using new capital stock estimates. Reg. Sci. Urban Econ. 25 (5), 607–630.
Cullison, W.E., 1993. Public investment and economic growth. Federal Reserve Bank Richmond Econ. Quart. 79 (4), 19–34.
Devarajan, S., Swaroop, V., Zou, H., 1996. The composition of public expenditure and economic growth. J. Monetary Econ. 37, 313–344.
Duffy-Deno, K.T., Eberts, R.W., 1991. Public infrastructure and regional economic development: a simultaneous equations approach. J. Urban Econ. 30 (3), 329–343.
Easterly, W., Rebelo, S., 1993. Fiscal Policy and Economic Growth: An Empirical Investigation. NBER Working Paper Series, No. 4499.
Eichengreen, B., Gupta, P., 2013. The two waves of service-sector growth. Oxford Econ. Pap. 65, 96–123.
Eisner, R., 1991. Infrastructure and regional economic performance. New England Econ. Rev., Federal Reserve Bank of, Boston (September/October), 47–58.
Erdil, E., Yetkiner, I.H., 2009. The granger-causality between health care expenditure and output: a panel data approach. Appl. Econ. 41 (4), 511–518.
Fedderke, J.W., Perkins, P., Luiz, J.M., 2006. Infrastructural investment in long-run economic growth: South Africa 1875–2001. World Dev. 34 (6), 1037–1059.
Fernald, J.G., 1999. Roads to prosperity? Assessing the link between public capital and productivity. Am. Econ. Rev. 89 (3), 619–638.
Fernandes, E., Pacheco, R.R., 2010. The causal relationship between GDP and domestic air passenger traffic in Brazil. Transp. Plann. Technol. 33 (7), 569–581.
Florens, J.P., Mouchart, M., 1982. Note on non-causality. Econometrica 50 (3), 583–591.
Garcia-Mila, T., McGuire, T.J., 1992. The contribution of publicly provided inputs to states' economies. Reg. Sci. Urban Econ. 22 (2), 229–241.
Garcia-Mila, T., McGuire, T., Porter, R.H., 1996. The effect of public capital in state-level production functions reconsidered. Rev. Econ. Stat. 78 (1), 177–180.
Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424–438.
Groote, P., Jacobs, J., Sturm, J.E., 1999. Output effects of transport infrastructure: The Netherlands, 1853–1913. Tijdschriftvoor Economische en Sociale Geografie 90 (1), 97–109.
Hansen, H., Rand, J., 2006. On the causal links between FDI and growth in developing countries. World Econ. 29 (1), 21–41.
Haque, M.E., Kim, D.H., 2003. Public Investment in Transportation and Communication and Growth: A Dynamic Panel Approach. The University of Manchester, Centre for Growth and Business Cycle Research Discussion Paper Series, 31.
Hausman, J., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1271.
Hausman, J., Taylor, W., 1981. Panel data and unobservable individual effects. Econometrica 49 (6), 1377–1398.
Hurlin, C., 2004a. Testing Granger Causality in Heterogeneous Panel Data Models with Fixed Coefficients. University of Orléans, Miméo.
Hurlin, C., 2004b. A Note on Causality Tests in Panel Data Models with Random Coefficients. University of Orléans, Miméo.
Hurlin, C., Venet, B., 2001. Granger Causality Tests in Panel Data Models with Fixed Coefficients. University Paris IX, Miméo.
Jiwattanakulpaisarn, P., Noland, R.B., Graham, D.J., 2010. Causal linkage between highways and sector-level employment. Transp. Res. Part A 44, 265–280.
Jiwattanakulpaisarn, P., Noland, R.B., Graham, D.J., Polak, J.W., 2009. Highway infrastructure and state-level employment: a causal spatial analysis. Pap. Reg. Sci. 88 (1), 133–159.
Jones, B.D., 1990. Public policies and economic growth in the American states. J. Polit. 52 (1), 219–233.
Kim, E., 2002. Determinants of optimal level of transportation infrastructure. J. Urban Plann. Develop. 128 (3), 150–163.
Kollias, C., Paleologou, S., 2013. Guns, highways and economic growth in the United States. Econ. Model. 30, 449–455.
Lakshmanan, T.R., 2007. The Wider Economic Benefits of Transportation: An Overview. OECD International Transport Forum, Joint Transportation Research Centre Discussion Paper, No: 2007-8.
Liddle, B., 2009. Long-run relationship among transport demand, income, and gasoline price for the US. Transp. Res. Part D 14, 73–82.
Liddle, B., 2012. The systemic, long-run relation among gasoline demand, gasoline price, income, and vehicle ownership in OECD countries: evidence from panel cointegration and causality modeling. Transp. Res. Part D 17, 327–331.
Lynde, C., Richmond, J., 1993. Public capital and long-run cost in U.K. manufacturing. Econ. J. 103 (419), 880–893.
Lu, Y., Weib, P., Wang, L., 2010. Co-integration analysis of freight volume, fuel oil price and GDP. J. Transp. Syst. Eng. Inform. Technol.
Meersman, H., Van de Voorde, E., 2013. The relationship between economic activity and freight transport. In: Ben-Akiva, Moshe E., Meersman, Hilde, Van De Voorde, Eddy (Eds.), Freight Transport Modelling. Emerald Group Publishing Limited, UK, pp. 17–44.
Mofidi, A., Stone, J.A., 1990. Do state and local taxes affect economic growth? Rev. Econ. Stat. 72 (4), 686–691.
Moonmaw, R.L., Mullen, J.K., Martin, W., 1995. The interregional impact of infrastructure capital. South. Econ. J. 61 (3), 830–845.
Munnell, A.H., 1990. Why has productivity declined? Productivity and public investment. New England Econ. Rev. (January/February), 3–22.
Munnell, A.H., Cook, L.M., 1990. How does public infrastructure affect regional economic performance. New England Econ. Rev. (September), 11–33.
Nadiri, M.I., Mamuneas, T.P., 1994. The effect of public infrastructure and R&D capital on the cost structure and performance of U.S. manufacturing industries. Rev. Econ. Stat. 76 (1), 22–37.
Owen, A.D., Phillips, G.D.A., 1987. The characteristics of railway passenger demand: an econometric investigation. J. Transp. Econ. Pol. 21 (3), 231–253.
Pradhan, R.P., Bagchi, T.P., 2013. Effect of transportation infrastructure on economic growth in India: the VECM approach. Res. Transp. Econ. 38, 139–148.
Randolph, S., Bogetic, Z., Hefley, D., 1996. Determinants of Public Expenditure on Infrastructure: Transportation and Communication. World Bank Policy Research Working Paper, No. 1661.
Reynolds, P.D., Maki, W., 1990. U.S. regional characteristics, new firms, and economic growth. Working Paper, University of Warwick, UK.
Romp, W., de Haan, J., 2007. Public capital and economic growth: a critical survey. Perspektiven der Wirtschaftspolitik 8, 6–52.
Santanu, M., Samyadip, C., 2012. GDP, railway freight, inflation & population density: An econometric quadrangular study in Indian context (1960–2009). Int. J. Business Econ. Manage. Res. 3 (4), 58–77.
Seitz, H., 1993. A dual economic analysis of the benefits of the public road network. Ann. Reg. Sci. 27 (3), 223–239.
Singletary, L., Henry, M., Brooks, K., London, J., 1995. The impact of highway investment on new manufacturing employment in South Carolina: a small region spatial analysis. Rev. Reg. Stud. 25 (summer), 37–55.

Tapio, P., 2005. Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. Transp. Policy 12, 137–151.
Xiong, H., Sun, Y., 2010. Analysis of co-integration and causality between freight traffic volume and economic growth in china. Syst. Eng. 9, 009.
Zhang, X., Fan, S., 2004. How productive is infrastructure? A new approach and evidence from rural india. Am. J. Agric. Econ. 86 (2), 492–501.
Zhou, J., Yang, L., Xu, Y., Liu, C., 2007. The economic performance of transportation infrastructure: an empirical study on the recent development of china. World Trans. Eng. Technol. Educ. UICEE 6 (1), 193–197.