Transport Policy 97 (2020) 19–25

Contents lists available at ScienceDirect

Transport Policy

journal homepage: http://www.elsevier.com/locate/tranpol

The Granger-causality between wealth and transportation: A panel data approach

Hakan Yetkiner[a,*], Mehmet Aldonat Beyzatlar[b,**]

[a] Department of Economics, Izmir University of Economics, 35330, Izmir, Turkey
[b] Department of Economics, Dokuz Eylül University, 35390, Izmir, Turkey

ARTICLE INFO

JEL classification:
C23
E01
R41

Keywords:
Granger-causality
Wealth
Income
Transportation
Freight
Passenger

ABSTRACT

This study examines the causal relationship between wealth and transportation. The study first develops two alternating theoretical frameworks between wealth and transportation: one in which transportation is demand-driven and one in which transportation has dual role, demand-driven and supply-driving. Next, the study undertakes Granger-causality estimations for a panel of 18 countries over the period 1970–2017. It is found that the dominant Granger-causality relationship is bidirectional for majority of countries. The study also shows that there is high consistency in the Granger-causality relationship between wealth and transportation, and income and transportation. The study has three important contributions: First, the relationship between wealth and transportation is shown both theoretically and empirically. Second, transportation is shown to have dual role in an economy. Finally, it is shown that the wealth-transportation relationship and the transport-income relationship are equally robust and consistent.

1. Introduction

Constant capital-output ratio is one of the stylized facts conjectured by Kaldor (1961) in his inventory of long-term properties of economic growth. Those familiar with economic growth theory would be profoundly aware that this condition is a key criterion for any growth model. What is less discussed in the literature is that physical capital is read as wealth under a closed economy with no government assumption, cf., Kurz (1968).[1] Therefore, the fixed capital-output ratio can also be interpreted as a fixed wealth-income ratio.[2] This interpretation opens new research horizons: if economic theory and/or empirical evidence implies a (fixed) relationship between income and a variable, then it must also exist (in some form) between wealth and that variable. It is our strongly-held belief that wealth acts as a very valuable variable in the field of transportation for at least five reasons (not all of which necessarily apply to our paper). First, the wealth effect on consumption expenditure has been a classic theme since the work of Modigliani (1971). In that respect, assuming that transportation is (only) a function of income disregards the possible effect of wealth on transportation. Second, income is subject to business cycles. Consequently, various transportation measures must also show procyclical behavior, as they are part of the generic aggregate consumption expenditure, cf., Table 2 in Lahiri et al. (2003). Then, any transportation study relying (only) on income data may reach statistically misleading conclusions due to bias caused by cycles. On the other hand, the stock variable characteristic of wealth makes it less inclined to cyclical movements. In that respect, the true relationship between transportation and wealth may also be valuable and informative. Third, wealth's high correlation with income designates that it can be used in robustness tests. Fourth, the use of wealth (rather than income) may avoid a potential endogeneity problem between income and transportation measures. Finally, the wealth elasticity of transportation may be as useful and informative as the income elasticity of transportation. It is unfortunate to observe that wealth, in contrast to income, lacks the research attention it deserves in the literature; one possible reason is that the prevalent wealth data is not as comprehensive as income. Fortunately, this is changing due to recent efforts, e.g., World Inequality Database.

This work studies the direction of causation between wealth and

* Corresponding author.
** Corresponding author.
E-mail addresses: hakan.yetkiner@ieu.edu.tr (H. Yetkiner), mehmet.beyzatlar@deu.edu.tr (M.A. Beyzatlar).

[1] Nonhuman wealth is the sum of the value of the household's physical assets and net financial assets. The latter is zero under closed economy with no government in a real economy.

[2] In a more recent study, Yetkiner and Nazlioğlu (2018) showed theoretically and empirically the long run constancy in wealth-income ratio.

https://doi.org/10.1016/j.tranpol.2020.07.004
Received 10 June 2019; Received in revised form 2 June 2020; Accepted 8 July 2020
Available online 11 July 2020
0967-070X/

transportation measures in order to show that the direction of causation here is as robust as the one between income and transportation measures. To this end, the study first develops two alternating theoretical relationships between wealth and transportation. Both models are extensions of the Solovian growth model. The first assumes that transportation expenditure is a component in aggregate demand, and its value is a fixed proportion of aggregate income. In that respect, the role attributed to transportation in this extension is essentially Keynesian, i.e., demand-sided.[3] The second assumes that transportation services, which are generated one-to-one by the transportation measure, also act as an essential factor of production in the aggregate production (aggregate studies in various fields, including housing, health, energy, and such often follows this strategy). The second extension, therefore, considers the supply-side role of transportation additionally. We interpret the second scenario as representing the idea of bidirectional causality, and the first as representing unidirectional economic causality from wealth to transportation.

Next, the study undertakes Granger-causality estimations for 18 countries in a panel data set covering the years from 1970 to 2017. The empirical analyses have two motivations. The first is to identify empirically the direction of economic causation: whether wealth stimulates transportation (demand sided) or bidirectional (demand sided and supply sided). The second is to show empirically that the relationship between income and transportation measures is echoed between wealth and transportation measures. Empirical analyses show that, across countries, the dominant Granger-causality relationship between wealth and transportation measures is bidirectional. Results also indicate a high consistency in the Granger-causality relationship between wealth and transportation measures, and between income and transportation measures.

To our knowledge, in the literature to date, there has been no effort to determine the direction of causation between wealth and transportation.[4] In contrast, there is considerable documentation on the Granger-causality relationship between variants of income and of transportation measures.[5] Two general observations can immediately be made. First, the literature offers contradictory evidence on the Granger-causality between transportation measures and income. Second, most causality studies focus on air transportation. Of these, several found that the direction of causality is from income to transportation, i.e., demand-sided. For example, Fernandes and Pacheco (2010), Marazzo et al. (2010), and Pacheco and Fernandes (2017) found that GDP precedes air transportation in Brazil. Similarly, Hakim and Merkert (2016) confirmed that GDP precedes air passenger traffic and air freight in eight South Asian countries.

Several other studies found that transportation is supply-sided. For example, Brida et al. (2016) demonstrated that Granger-causality worked from air transportation to GDP in Italy for the period 1971–2012. Mukkala and Tervo (2013), constructed a panel data set by classifying eighty-six European regions into three groups of equal size: peripheral, intermediate, and core, showed that, for peripheral regions, the direction of Granger-causality is from air traffic to regional growth. Hu et al. (2015), undertaking panel VECM analysis using data from Chinese 29 provinces, found that the direction of causality is from domestic air traffic to GDP in the short run. Tong and Yu (2018) showed a unidirectional causality from freight transportation per capita (in metric ton-km) to GDP per capita in the more affluent eastern region in China. Button and Yuan (2013) demonstrated that the direction of causality is also from air freight to income for the US for the 1990–2009 period.

Finally, numerous studies found evidence of (dominantly) bidirectional relationship, including Baker et al. (2015), Beyzatlar et al. (2014), Chang and Chang (2009), Chi and Baek (2013), Hu et al. (2015), Pradhan and Bagchi (2013), Tong and Yu (2018), and Yao (2005). For example, bidirectional causal relationships were found between domestic air traffic and GDP in the long-run by Hu et al. (2015), between air passenger movements and real income for Australia by Baker et al. (2015), and between freight transportation per capita and GDP per capita for less developed regions in China by Tong and Yu (2018).

We propose two fundamental reasons for the inconclusiveness of the existing literature. First, heuristically speaking, the majority, if not all the cited studies, lack a strong theoretical basis. Second, stemming from this lack of theory, also there are substantial variations in the variables assumed representing transportation and income; hence, the data varies substantially in several aspects, including the unit of measure, aggregation level, time span, etc. (in connection with this, the majority of Granger-causality analyses focused on air transportation data). The study therefore has three important contributions: First, the relationship between wealth and transportation is shown both theoretically and empirically. Second, it is shown that the dominant Granger-causality between transportation and wealth is dominantly bidirectional, that is, transportation has a dual role, demand-driven and supply-driving, in an economy. Finally, it is shown that the relationship between wealth and transportation is as consistent and robust as the one between transportation and income. The study has two important policy implications. First, the transportation sector, as a key enabler of economic activities, facilitates access of suppliers and demanders to every type of market and therefore policymakers must ensure uninterrupted transportation service. Second, the dominant bidirectional causality between wealth and transportation sector implies that "better" transportation may act against the law of diminishing marginal physical product that capital (wealth) is subject à la technological progress. This characteristic of transportation again necessitates policymakers to ensure uninterrupted transportation service in an economy.

The paper is structured as follows. Section 2 presents theory, data, methodology, and empirical findings. Our analyses show that the dominant Granger-causality relationship between wealth and transportation measures is bidirectional at country-level. Section 3 concludes.

2. Theory, data, methodology, and empirical results

2.2. Theoretical representation

Let us assume a Solovian economy under a closed economy without government assumption. Suppose that aggregate demand AD is $AD_t = (C_t + TR_t) + I_t$, where C is non-transportation consumption expenditure, TR is transportation expenditure, I is gross investment expenditure, and subscript t index time. We assume that $C_t = mpc \cdot Y_t$and $TR_t = mptr \cdot Y_t$, where mpc is the marginal propensity to consume out of income and $mptr$is the marginal propensity to transport out of income. Macroeconomic equilibrium implies that $s_K \cdot Y_t = I_t$, where $s_K \equiv 1 - mpc - mptr$. Assume that $Y_t = K_t^{\alpha} \cdot L_t^{1-\alpha}$, where K is physical capital, L is labor (population), and α is the production elasticity of physical capital. Applying Occam's razor, neither productivity parameter nor technological progress are introduced in the model. Finally, we assume that $L_t = L_0 \cdot e^{nt}$, where n is the growth rate of population. Given $I_t \equiv \dot{K}_t + \delta \cdot K_t$, the fundamental equation of growth becomes $\dot{K}_t = s_K \cdot K_t^{\alpha} \cdot L_t^{1-\alpha} - \delta \cdot K_t$, where δ is the depreciation rate. The long-run equilibrium of this model implies that $k_{ss} = \left(\frac{s_K}{n+\delta}\right)^{\frac{1}{1-\alpha}}$, $y_{ss} = k_{ss}^{\alpha}$and $tr_{ss} = mptr \cdot y_{ss}$, where k is capital per capita, y is income per capita, tr is the real transportation expenditure per capita, and ss represents steady-state. The golden rule of saving rate s_K^{Gold} which maximizes steady state level of transportation

[3] There is only an indirect effect of transportation on wealth and income.

[4] We found only Alperovich and Machnes (1994) which considers the role of financial and nonfinancial wealth in explaining demand for international air travel from Israel.

[5] Our review excludes Granger-causality studies on transportation infrastructure, as this is a stock variable. See the comprehensive literature review in Maparu and Mazumder (2017) and Saidi et al. (2018).

$tr_{ss}$is $s_K^{Gold} = \alpha(1-mpc)$, which implies the golden $mptr$ as $mptr^{Gold} = (1-\alpha)(1-mpc)$. The role of transportation in the model economy is essentially demand-sided, as the determinants of capital (=wealth) and income have a direct role in transportation demand, but transportation has only an indirect role in production (=supply). The demand-driven role of transportation leads to lower steady state values of physical capital per capita and income per capita (compared to original no-transportation Solow model), and states that capital per capita and income per capita decrease when marginal propensity to transport increases, that is, $\frac{\partial k_{ss}}{\partial mptr} < 0$ and $\frac{\partial y_{ss}}{\partial mptr} < 0$. If it is this model that characterizes empirical regularity, then data must generate a unidirectional causality from wealth to transportation, or income to transportation.

Alternatively, let us suppose that the production function is defined as $Y_t = K_t^{\alpha} \cdot TR_t^{\beta} \cdot L_t^{1-\alpha-\beta}$, that is, transportation is essential in aggregate production activity and β is the production elasticity of transportation.[6] Clearly, it is the service generated by the physical quantity of the transportation which is the input in the production process. For matter of convenience, we assume that there is one-to-one correspondence between the physical quantity and the service generated by the physical quantity. Under this scenario, the long-run equilibrium implies that $k_{ss} = mptr^{\frac{\beta}{1-\alpha-\beta}} \cdot \left(\frac{s_K}{n+\delta}\right)^{\frac{1-\beta}{1-\alpha-\beta}}$, $y_{ss} = mptr^{\frac{\beta}{1-\alpha-\beta}} \cdot \left(\frac{s_K}{n+\delta}\right)^{\frac{\alpha}{1-\alpha-\beta}}$ and $tr_{ss} = mptr^{\frac{1-\alpha}{1-\alpha-\beta}} \cdot \left(\frac{s_K}{n+\delta}\right)^{\frac{\alpha}{1-\alpha-\beta}}$. Then, the role of transportation is both demand-sided and supply-sided, as determinants of capital (=wealth) and income has a direct role in transportation and vice versa. The dual role (demand-driven and supply-driving) of transportation is also reflected in the impact of a change in marginal propensity to transport on the steady state values of physical capital per capita and income per capita: $\frac{\partial k_{ss}}{\partial mptr} > 0$if $\frac{s_K}{mptr} > \frac{1-\beta}{\beta}$ and $\frac{\partial y_{ss}}{\partial mptr} > 0$if $\frac{s_K}{mptr} > \frac{\alpha}{\beta}$, that is, marginal propensity to save over marginal propensity to transport must be greater than the ratio of production elasticity of non-transport inputs over production elasticity of transportation and the ratio of production elasticity of physical capital over production elasticity of transportation. Interestingly, the golden rule of saving rate s_K^{Gold} which maximizes steady state level of transportation tr_{ss} is again $s_K^{Gold} = \alpha(1-mpc)$, which also implies $mptr^{Gold} = (1-\alpha)(1-mpc)$. If it is this model that characterizes empirical regularity, then data must yield bidirectional causation between wealth and transportation, and income and transportation. The Granger causality analyses provided below will highlight which model that the data supports.

2.2. Data

This study covers 18 countries for the period 1970–2017.[7] Data was obtained from two different sources. Wealth per capita and income per capita are taken from the World Inequality Database. Wealth per person is the market-value national wealth divided by total population (all ages) in 2017 constant USD (PPP), and income per person is the gross domestic product divided by total population (all ages) in 2017 constant USD (PPP). Under transportation, two variables have been considered: total inland freight per capita in tonne-km and total inland passenger per capita in passenger-km. These represent the physical movements of goods and individuals. Both were obtained from the OECD Stat Extracts Database. For all variables, we take the natural logarithms, check for cross-sectional dependence,[8] and take the first difference to eliminate unit-roots (see Table 1).[9]

2.3. Methodology

The methodology of the paper is based on Hurlin and Venet (2001), Hurlin (2004), and Hansen and Rand (2006). The following equations are estimated to test the direction of causality from wealth to transportation Equation (1) and from transportation to wealth Equation (2):

$$\text{transportation}_{i,t} = \sum_{k=1}^{p} \alpha_k \text{transportation}_{i,t-k} + \sum_{k=0}^{p} \theta_k \text{wealth}_{i,t-k} + u_{i,t} \tag{1}$$

$$\text{wealth}_{i,t} = \sum_{k=1}^{p} \beta_k \text{wealth}_{i,t-k} + \sum_{k=0}^{p} \vartheta_k \text{transportation}_{i,t-k} + e_{i,t} \tag{2}$$

where index i refers to the country ($i = 1,\dots,N$), $t$to the time period ($t = 1,\dots,T$), p to the maximum lag, and k to the lag. We assume that $u_{i,t}$ in Equation (1) and $e_{i,t}$ in Equation (2) are normally distributed for all countries. The autoregressive coefficients α_k in Equation (1) and β_k in Equation (2) and the regression coefficients' slopes θ_k in Equation (1) and ϑ_k in Equation (2) are constant $\forall\ k \in [1, p]$. It is also assumed that parameters α_k in Equation (1) and β_k in Equation (2) are identical for all countries, whereas the regression coefficient slopes θ_k in Equation (1) and ϑ_k in Equation (2) could have an individual dimension.

According to Hurlin and Venet (2001), working with panel data improves the efficiency of Granger-causality, whereas the issue of heterogeneity between individuals must necessarily be put into perspective. For this reason, they proposed a three-step testing procedure shown in Table 2 to identify causality relationship in the context of heterogeneity[10].

The first step, testing Homogenous and Instantaneous Non-causality hypothesis (HINC, hereafter), aims at determining whether or not the θ_k's in Equation (1) and ϑ_k's in Equation (2) are null for all individual i and all lag k. The second step is testing the Homogenous Causality hypothesis (HC, hereafter) if HINC is rejected. HC aims to test whether θ_k's in Equation (1) and ϑ_k's in Equation (2) are equal for all lag k, and are statistically different from zero. The third step is testing the

Table 1
Descriptive statistics.

Variables[a]	# of Obs.	Mean	Median	Minimum	Maximum
Freight	735	8.289	8.197	6.768	10.161
Passenger	697	8.994	9.242	6.126	9.886
Income	884	9.996	10.159	6.741	10.846
Wealth	627	11.571	11.643	8.252	12.622

[a] Freight is total inland freight per capita in tonne-km; Passenger is total inland passenger per capita in passenger-km; Income is gross domestic product per capita in constant (2017) USD (PPP); and Wealth is market-value national wealth per capita in constant (2017) USD (PPP). All variables are in per capita and natural log form.

[6] One immediate question on our definition of transportation is that some studies assume that transportation is a part of total factor productivity rather than an input. We believe that the current COVID-19 pandemic showed that transportation is not only demand-driven, but it has also a supply-driving nature. In the countries in which (some) transportation is substantially limited, production fell because labor (and intermediate material) was excluded from production activities. If the supply nature of transportation was only via productivity, production in those countries have remained much more stable.

[7] Australia, Canada, China, Czechia, Denmark, Finland, France, Germany, Greece, Italy, Japan, Republic of Korea, Mexico, Netherlands, Spain, Sweden, United Kingdom, and USA. The country list is determined by wealth data availability.

[8] According to panel cross-section dependence tests, the null hypothesis of no cross-section dependence is failed to be rejected, which allows us to perform first-generation panel unit-root tests.

[9] According to individual and common panel unit-root tests, all series indicate that the null hypothesis of stationarity is rejected in level and accepted in first differences, i.e., all variables are found to be integrated of order 1.

[10] Please refer to Erdil and Yetkiner (2009) and Beyzatlar et al. (2014) for details.

Table 2
Types of Causality tested in a Panel Data Framework.

Test	Test hypothesis	Test statistics
HINC	$H_0: \theta_k = 0 \ \forall i \in [1, N], \ \forall k \in [0, p], i \neq j$ $H_1: \theta_k \neq 0 \ \exists (i, k)$ $H_0: \vartheta_k = 0 \ \forall i \in [1, N], \ \forall k \in [0, p], i \neq j$ $H_1: \vartheta_k \neq 0 \ \exists (i, k)$	$F_{HINC} = \frac{(SSR_r - SSR_u)/(N_p)}{SSR_u/[NT - N(1+p) - p]}$
HC	$H_0: \theta_k^i = \theta_k^j \ \forall i, j \in [1, N], \ \forall_k \in [0, p]$ $H_1: \theta_k^i \neq \theta_k^j \ \exists (i, j, k)$ $H_0: \vartheta_k^i = \vartheta_k^j \ \forall i, j \in [1, N], \ \forall_k \in [0, p]$ $H_1: \vartheta_k^i \neq \vartheta_k^j \ \exists (i, j, k)$	$F_{HC} = \frac{(SSR_r' - SSR_u)/[p(N-1)]}{SSR_u/[NT - N(1+p) - p]}$
HENC	$H_0: \theta_i^k = 0 \ \forall i \in [1, N], \ \forall_k \in [0, p]$ $H_1: \theta_i^k \neq 0 \ \forall i \in [1, N], \ \forall_k \in [0, p]$ $H_0: \vartheta_i^k = 0 \ \forall i \in [1, N], \ \forall_k \in [0, p]$ $H_1: \vartheta_i^k \neq 0 \ \forall i \in [1, N], \ \forall_k \in [0, p]$	$F_{HENC} = \frac{(SSR_r'' - SSR_u)/p}{SSR_u/[NT - N(1+p) - p]}$

Note: HINC, Homogenous and Instantaneous Non-Causality hypothesis; HC, Homogenous Causality hypothesis; HENC, Heterogeneous Non-Causality hypothesis; SSR_u, Sum of Squared Residuals Unrestricted for the respective null hypothesis; SSR_r, Sum of Squared Residuals Restricted for the respective null hypothesis.

Heterogeneous Non-causality hypothesis (HENC, hereafter) if HC is also rejected, demonstrating that the causality process is non-homogenous in the panel data dimension (Hurlin, 2004). Causality relationship can also be found in cross-sectional dimension, therefore, the nullity of θ_k's in Equation (1) and ϑ_k's in Equation (2) are tested for each cross-sectional unit in HENC. The rejection of the null hypothesis of country-level no-causality shows the existence of causality relationship for at least some countries.

2.4. Empirical findings

The methodology suggests three steps in sequence: HINC (panel data), HC (panel data) and HENC (time-series). In accordance with the Hausman (1978) test, Equations (1) and (2) are estimated with fixed effects to check panel causality, and the results are presented in Table 3. The null hypothesis of HINC is rejected at 1% or 5% significance levels, which reveals that a causality relationship exists between wealth and transportation measures. Next, the null hypothesis of whether the causality is homogenous for all countries in the panel dimension (HC) is tested, and the null hypothesis is again rejected at 1% or 5% significance levels.

The same procedure is repeated after wealth is replaced by income in order to identify the nature of the causality relationship between income and transportation for the same countries over the period 1970–2017. Both hypotheses are rejected in both directions, consistent with wealth, as reported in Table 4.

Concluding absence of homogenous causality, we turn into heterogeneous causality (HENC), which requires testing the causality between

Table 3
Homogeneous causality between wealth and transportation.

	Eqns.	HINC	HC
Causality from wealth to freight	(1)	12.254***	16.423***
Causality from freight to wealth	(2)	9.442***	3.277**
Causality from wealth to passenger	(1)	2.441**	2.536**
Causality from passenger to wealth	(2)	5.353***	2.023**

Note: HINC, Homogenous and Instantaneous Non-Causality hypothesis; HC, Homogenous Causality hypothesis; *** and ** Reject H_0 at 1% and 5% levels of significance, respectively.

wealth and transportation measures, and income and transportation measures for each of 17 countries for the period 1970–2017.[11] For this purpose, Equations (1) And (2) are modified as follows:

$$\text{transportation}_t = \sum_{m=1}^{r} \alpha_l \text{transportation}_{t-m} + \sum_{m=0}^{r} \theta_m \text{wealth}_{t-m} + u_t \tag{3}$$

$$\text{wealth}_t = \sum_{m=1}^{r} \beta_m \text{wealth}_{t-m} + \sum_{m=0}^{r} \vartheta_m \text{transportation}_{t-m} + e_t \tag{4}$$

where index $t$refers to the time period ($t = 1, \ldots, T$), r to the maximum lag, and m to the lag. Estimation of Equations (3) And (4) reveal whether there is Granger-causality for each country, where θ_m and ϑ_m vary across countries: the rejection of the null hypothesis of country-level no-causality signs the existence of Granger-causality between the variables at the country-level. The results of the HENC are summarized in Table 5.[12]

Column (1) presents the Granger-causality results between wealth and freight. Our analyses show that for the majority, 15 out of 17countries, Granger-causality is bidirectional. Column (2) shows that the dominant Granger-causality between income and freight is also bidirectional in our sample of countries.[13] A comparison of columns (1) and (2) indicate that Granger-causality results are consistent for 14 countries, and 13 are bidirectional. Column (1) also shows that Granger-causality is supply sided in Italy, but demand-sided in Greece. Column (3) depicts that the dominant Granger-causality between wealth and passenger mobility is bidirectional, 11 out of 17 countries. We observe Granger-causality from passenger mobility to wealth for Australia, Greece, Italy, and Mexico. Column (4) shows that the dominant Granger-causality between income and passenger mobility is also bidirectional.[14] A comparison of columns (3) and (4) indicate that Granger-causality results are consistent for 12 countries. We observe Granger-causality is demand-sided for Finland and Mexico, à la Fernandes and Pacheco (2010), Hakim and Merkert (2016), Marazzo et al. (2010), and Pacheco and Fernandes (2017), and supply-sided for China, à la Arvin et al. (2015), Hu et al. (2015), and Mukkala and Tervo (2013).

2.5. Robustness check

In this subsection, we undertake robustness analysis by using an

Table 4
Homogeneous causality between income and transportation.

	Eqns.	HINC	HC
Causality from income to freight	(1)	39.256***	28.320***
Causality from freight to income	(2)	37.163***	29.895***
Causality from income to passenger	(1)	6.201***	2.954**
Causality from passenger to income	(2)	4.339***	3.749***

Note: HINC: Homogenous and Instantaneous Non-Causality hypothesis. HC: Homogenous Causality hypothesis. *** and ** Reject H_0 at 1% and 5% levels of significance, respectively.

[11] We eliminated Republic of Korea from individual causality analysis, as the degrees of freedom were very low for both restricted and unrestricted regressions.

[12] The detailed F-statistics for HENC tests between wealth and transportation and income and transportation can be seen in the appendix in Table A1 and Table A2, respectively.

[13] This result is in line with the literature, e.g., Beyzatlar et al. (2014) for EU-15 countries, Lean et al. (2014) and Tong and Yu (2018) for China, and Chi and Baek (2013) for USA.

[14] This result is in line with the literature, e.g., Baker et al. (2015) for Australia, Brida et al. (2016) for Mexico, Chi and Baek (2013) for USA, and-Beyzatlar et al. (2014) for EU-15 countries.

Table 5
The comparison of HENC results between wealth and income.

Country	(1) W and F	(2) I and F	(3) W and P	(4) I and P
Australia	**bidirectional**	**bidirectional**	P to W	bidirectional
Canada	bidirectional	I to F	bidirectional	no causality
China	**bidirectional**	**bidirectional**	bidirectional	P to I
Czechia	bidirectional	I to F	**bidirectional**	**bidirectional**
Denmark	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Finland	**bidirectional**	**bidirectional**	no causality	I to P
France	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Germany	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Greece	W to F	no causality	P to W	bidirectional
Italy	F to W	bidirectional	P to W	bidirectional
Japan	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Mexico	**bidirectional**	**bidirectional**	P to W	I to P
Netherlands	**bidirectional**	**bidirectional**	**no causality**	**no causality**
Spain	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Sweden	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
UK	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
USA	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**

Note: W, Wealth; I, Income; F, Freight; P, Passenger.

alternative proxy for wealth, namely the capital stock. Our aim is to ensure that there is no ambiguity in the direction of causality between wealth and transportation measures, in the Granger sense. For this purpose, we use capital stock per capita (in constant 2011 USD). The data has been compiled from the Penn World Table version 9.1 database for the same 18 countries for the period 1970–2017. After (i) no cross-sectional dependency is verified, (ii) capital stock is purified from the unit-root with first-generation panel unit-root tests, and (iii) fixed effects model is fitted, exactly the same procedure (HINC, HC, and HENC) is followed. In accordance with results presented in Table 6, HINC and HC are again rejected.

Next, HENC is estimated and the null hypothesis of country-level no-causality is rejected (the detailed F-statistics are given Table A3). In Table 7 below, we compare HENC results of wealth and capital stock.[15] Columns (1) and (2) and columns (3) and (4) indicate that wealth and capital stock generate a similar pattern in terms of Granger-causality: 14 out of 17 countries show bidirectional causality between capital stock and freight mobility, as well as between wealth and freight mobility. Similarly, 11 out of 17 countries generate identical direction of causality between capital stock and passenger mobility, wealth and passenger, of which 10 out of 11 are bidirectional.

Our robustness check indicates that bidirectional causality is the dominant direction for both wealth measures. This result indicates that transportation has a dual role in an economy, demand-driven and supply-driving. On the one hand, wealth (and income) enhances transportation mobility; on the other, transportation mobility is itself an important input to wealth (and income). The recent COVID-19 epidemic

Table 6
Homogeneous causality between capital stock and transportation.

	Eqns.	HINC	HC
Causality from capital stock to freight	(1)	14.189***	13.174***
Causality from freight to capital stock	(2)	11.711***	9.424***
Causality from capital stock to passenger	(1)	15.529***	12.993***
Causality from passenger to capital stock	(2)	6.262***	3.488***

Note: HINC, Homogenous and Instantaneous Non-Causality hypothesis; HC, Homogenous Causality hypothesis. ***, ** and * Reject H_0 at 1%, 5% and 10% levels of significance, respectively.

[15] We again eliminated Republic of Korea from individual-level causality analysis, as the degrees of freedom were very low for both restricted and unrestricted regressions.

Table 7
The comparison of HENC results between wealth and capital stock.

Country	(1) W and F	(2) CS and F	(3) W and P	(4) CS and P
Australia	bidirectional	CS to F	P to W	CS to P
Canada	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
China	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Czechia	**bidirectional**	**bidirectional**	bidirectional	CS to P
Denmark	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Finland	**bidirectional**	**bidirectional**	no causality	bidirectional
France	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Germany	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Greece	W to F	no causality	P to W	no causality
Italy	F to W	bidirectional	**P to W**	**P to CS**
Japan	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Mexico	**bidirectional**	**bidirectional**	P to W	CS to P
Netherlands	**bidirectional**	**bidirectional**	no causality	P to CS
Spain	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
Sweden	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
UK	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**
USA	**bidirectional**	**bidirectional**	**bidirectional**	**bidirectional**

Note: W, Wealth; CS, Capital Stock; F, Freight; P, Passenger.

clearly indicated that latter characteristics of transportation. The lockdown on passenger mobility and constraints on freight mobility led to a sharp decline in production, income and wealth accumulation. That is because transportation mobility services are more than a component of overall efficiency of economies. They are a vital input without which no economy can sustain itself.

3. Concluding remarks and policy implications

The transportation literature has focused on the role of income in explaining transportation. The constancy of the capital-output ratio in the long-run suggests that a similar role can be attributed to wealth (=capital) in understanding transportation. This study was an application of the idea advanced above: it studied the direction of causation between wealth and transportation measures. The study first presented two alternating theoretical results on the role of transportation: one is essentially demand-sided, and the other is both demand- and supply-sided. Next, the study undertook Granger-causality estimations for 18 countries in a panel data set, covering the years 1970–2017. Empirical analyses showed that the Granger-causality relationships between wealth and transportation measures are highly consistent with those between income and transportation measures across countries, and that the dominant relationship is bidirectional.

The study has two important policy implications. First, through its physical networks and services, the transportation sector is a key enabler of economic activities, as it facilitates the access of suppliers and demanders to markets, including the labor market and international markets (international trade). The recent COVID-19 epidemic clearly indicated the indispensable role of transportation: limitations on passenger and freight mobility led to a sharp decline not only in demand, but also in overall production activities and trade. We argue that this unique role of transportation in an economy necessitates that policymakers must give priority to prevent interruption to transportation network and services. This is the first policy implication of our work.

Second, the dominant bidirectional causality between wealth and transportation sector implies that "better" transportation may act against the law of diminishing marginal physical product that capital (wealth) is subject à la technological progress. We argue that limitations on passenger and freight mobility during the recent COVID-19 epidemic is the other reason why output falls for a given capital stock: the limitations led to a downward shift of marginal physical product of capital. This (unstudied) role of transportation also necessitates policymakers to give priority to prevent interruption to transportation network and services. Our conclusion is that transportation is a cause and effect in an economy.

CRediT authorship contribution statement

Hakan Yetkiner: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Mehmet Aldonat Beyzatlar:** Software, Validation, Formal analysis, Investigation, Resources, Data curation, Visualization.

Appendix

Table A1
Heterogeneous causality between wealth and transportation.

Country	Null: Heterogeneous Non-Causality (HENC)			
	W to F	F to W	W to P	P to W
Australia	4.218**	4.843**	1.693	3.058*
Canada	7.348***	7.242***	14.638***	13.196***
China	8.753***	6.921***	10.783***	6.964***
Czechia	3.589**	3.849**	3.525**	12.982**
Denmark	3.163*	9.308***	11.134***	9.726***
Finland	12.379*	10.853*	0.348	0.325
France	4.408**	4.315**	2.517**	3.229**
Germany	16.939***	7.844***	7.886***	7.884***
Greece	2.462*	0.734	1.071	15.983***
Italy	0.615	6.588***	0.769	4.698***
Japan	6.907***	2.558**	7.447***	5.382***
Mexico	4.261***	6.740***	2.233	3.241**
Netherlands	3.994**	12.893***	0.766	0.449
Spain	11.558***	5.859***	12.353***	12.514***
Sweden	2.160*	3.327**	4.208**	2.905**
UK	5.143***	7.163***	2.927**	3.135**
USA	3.578**	4.768***	3.811**	5.789***

Note: W, Wealth; F, Freight; P, Passenger. ***, ** and * Reject H_0 at 1%, 5% and 10% levels of significance, respectively.

Table A2
Heterogeneous causality between income and transportation.

Country	Null: Heterogeneous Non-Causality (HENC)			
	I to F	F to I	I to P	P to I
Australia	3.742**	3.412**	6.655***	3.285**
Canada	4.144**	0.784	3.281	0.566
China	3.000*	2.392*	0.285	3.423**
Czechia	3.005*	0.546	2.828*	4.687**
Denmark	8.824***	11.126***	8.548***	3.409**
Finland	8.590***	5.680***	17.108***	1.637
France	9.497***	6.074***	3.131***	3.900***
Germany	42.391***	59.829***	5.839***	5.715***
Greece	0.416	0.402	4.024***	4.128***
Italy	5.386***	3.757**	5.718***	4.126***
Japan	4.797**	3.898**	5.134**	16.871***
Mexico	6.362***	8.415***	5.147***	1.362
Netherlands	10.333***	19.759***	1.056	1.338
Spain	3.825*	3.332*	11.745***	3.265**
Sweden	3.059**	4.035**	5.296***	3.009*
UK	11.255***	8.309***	8.906***	4.687**
USA	13.624***	16.715***	4.245**	6.429***

Note: I, Income; F, Freight; P, Passenger. ***, ** and * Reject H0 at 1%, 5% and 10% levels of significance, respectively.

Table A3
Heterogeneous causality between capital stock and transportation.

Country	Null: Heterogeneous Non-Causality (HENC)			
	CS to F	F to CS	CS to P	P to CS
Australia	3.304**	0.693	2.612*	0.266
Canada	6.987***	4.632**	6.383*	6.209**
China	4.872**	7.010***	4.274**	6.160**
Czechia	3.314**	3.238**	5.832**	2.556
Denmark	6.743***	10.758***	5.748***	7.833***
Finland	3.482**	3.053**	8.098***	2.667*
France	14.794***	15.170***	5.845***	6.478***
Germany	7.398***	16.363***	8.778***	8.688***
Greece	0.218	0.476	0.932	0.949

(*continued on next page*)

Table A3 (*continued*)

Country	Null: Heterogeneous Non-Causality (HENC)			
	CS to F	F to CS	CS to P	P to CS
Italy	6.230***	6.849***	1.435	3.389**
Japan	3.546**	3.986***	2.821**	3.756**
Mexico	8.682***	7.503***	3.131**	1.659
Netherlands	13.367***	16.354***	1.665	4.696***
Spain	2.685*	2.975**	3.693**	4.101**
Sweden	2.893*	4.449**	12.027***	6.244***
UK	14.238***	15.492***	7.801***	10.569***
USA	3.643**	4.724**	4.293**	3.439**

Note: CS, Capital Stock; F, Freight; P, Passenger. ***, ** and * Reject H0 at 1%, 5% and 10% levels of significance, respectively.

References

Alperovich, G., Machnes, Y., 1994. The role of wealth in the demand for international air travel. J. Transport Econ. Pol. 28, 163–173.

Arvin, M.B., Pradhan, R.P., Norman, N.R., 2015. Transportation intensity, urbanization, economic growth, and CO2 emissions in the G-20 countries. Utilities Policy 35, 50–66.

Baker, D., Merkert, R., Kamruzzaman, M., 2015. Regional aviation and economic growth: cointegration and causality analysis in Australia. J. Transport Geogr. 43, 140–150.

Beyzatlar, M.A., Karacal, M., Yetkiner, H., 2014. Granger-causality between transportation and GDP: a panel data approach. Transport. Res. Pol. Pract. 63, 43–55.

Brida, J.G., Bukstein, D., Zapata-Aguirre, S., 2016. Dynamic relationship between air transport and economic growth in Italy: a time series analysis. Int. J. Aviat. Manag. 3 (1), 52–67.

Button, K., Yuan, J., 2013. Airfreight transport and economic development: an examination of causality. Urban Stud. 50 (2), 329–340.

Chang, Y.H., Chang, Y.W., 2009. Air cargo expansion and economic growth: finding the empirical link. J. Air Transport. Manag. 15 (5), 264–265.

Chi, J., Baek, J., 2013. Dynamic relationship between air transport demand and economic growth in the United States: A new look. Transp. Pol. 29, 257–260.

Erdil, E., Yetkiner, H., 2009. The Granger-causality between health care expenditure and output: a panel data approach. Appl. Econ. 41 (4), 511–518.

Fernandes, E., Pacheco, R.R., 2010. The causal relationship between GDP and domestic air passenger traffic in Brazil. Transport. Plann. Technol. 33 (7), 569–581.

Hakim, M.M., Merkert, R., 2016. The causal relationship between air transport and economic growth: empirical evidence from South Asia. J. Transport Geogr. 56, 120–127.

Hansen, H., Rand, J., 2006. On the causal links between FDI and growth in developing countries. World Econ. 29 (1), 21–41.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica J. Econ. Soc. 46 (6), 1251–1271.

Hu, Y., Xiao, J., Deng, Y., Xiao, Y., Wang, S., 2015. Domestic air passenger traffic and economic growth in China: evidence from heterogeneous panel models. J. Air Transport. Manag. 42, 95–100.

Hurlin, C., 2004. Testing Granger Causality in Heterogeneous Panel Data Models with Fixed Coefficients. University of Orléans, Miméo.

Hurlin, C., Venet, B., 2001. Granger Causality Tests in Panel Data Models with Fixed Coefficients. University, Miméo.

Kaldor, N., 1961. Capital accumulation and economic growth. In: Hague, D.C. (Ed.), The Theory of Capital, International Economic Association Series. Palgrave Macmillan, London, pp. 177–222.

Kurz, M., 1968. Optimal economic growth and wealth effects. Int. Econ. Rev. 9 (3), 348–357.

Lahiri, K., Stekler, H., Yao, W., Young, P., 2003. Monthly output index for the US transportation sector. J. Transport. Stat. 6 (2/3).

Lean, H.H., Huang, W., Hong, J., 2014. Logistics and economic development: experience from China. Transport Pol. 32, 96–104.

Maparu, T.S., Mazumder, T.N., 2017. Transport infrastructure, economic development and urbanization in India (1990–2011): is there any causal relationship? Transport. Res. Pol. Pract. 100, 319–336.

Marazzo, M., Scherre, R., Fernandes, E., 2010. Air transport demand and economic growth in Brazil: a time series analysis. Transport. Res. E Logist. Transport. Rev. 46 (2), 261–269.

Modigliani, F., 1971. Monetary policy and consumption: linkages via interest rate and wealth effects in the FMP model, consumer spending and monetary policy: the linkages. In: Federal Reserve Bank of Boston Conference Series, vol. 5.

Mukkala, K., Tervo, H., 2013. Air transportation and regional growth: which way does the causality run? Environ. Plann. 45 (6), 1508–1520.

Pacheco, R.R., Fernandes, E., 2017. International air passenger traffic, trade openness and exchange rate in Brazil: a Granger causality test. Transport. Res. Pol. Pract. 101, 22–29.

Pradhan, R.P., Bagchi, T.P., 2013. Effect of transportation infrastructure on economic growth in India: the VECM approach. Res. Transport. Econ. 38 (1), 139–148.

Saidi, S., Shahbaz, M., Akhtar, P., 2018. The long-run relationships between transport energy consumption, transport infrastructure, and economic growth in MENA countries. Transport. Res. Pol. Pract. 111, 78–95.

Tong, T., Yu, T.E., 2018. Transportation and economic growth in China: a heterogeneous panel cointegration and causality analysis. J. Transport Geogr. 73, 120–130.

Yao, V.W., 2005. The causal linkages between freight and economic fluctuations. Int. J. Transp. Econ. 32 (2), 143–159.

Yetkiner, H., Nazlioglu, S., 2018. Is there an optimal level of housing wealth in the long-run? Theory and evidence. Res. Int. Bus. Finance 46, 257–267.