Transportation Services, Financial Market, and Industrial Production in the US: Evidence from the Recursive Evolving Causality Test

ABD'de Ulaşım Hizmetleri, Finansal Piyasa ve Endüstriyel Üretim: Özyinelemeli Nedensellik Testinden Elde Edilen Bulgular

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Abstract

This paper examines the relationship between Transportation Services Index (TSI), Dow Jones Transportation Average Index (DJT), and Industrial Production Index (IND) for the United States of America by using monthly data in the period from January 2000 to March 2019. The long-run nexus is demonstrated through the cointegration test and dynamic cointegrating regression (Dynamic OLS), both with structural breaks. The results show that the long-run relations proved by both tests from IND to TSI, IND to DJT, and two-sided between DJT and TSI. More importantly, the Granger-causality relationship is revealed with the forward, rolling, and recursive evolving window algorithms. This is the first study in the literature investigating the causality ties in transportation measures using the novel econometric methodology, following the algorithms. The rolling and recursive causality results detect bi-directional causality between IND and TSI, IND and DJT, and TSI and DJT. Then we come up with some suggestions that the transportation institutions should modulate the transportation sector's financial structure and intensify to adjust industry structures within transportation mobility before, during, and after recessionary periods.

Keywords: Transportation services index, Dow Jones transportation index, industrial production index, recursive evolving causality

Paper Type: Research

Öz

Bu makale, Amerika Birleşik Devletleri için Ulaşım Hizmetleri Endeksi (TSI), Dow Jones Ulaşım Ortalama Endeksi (DJT) ve Endüstriyel Üretim Endeksi (IND) arasındaki ilişkiyi Ocak 2000'den Mart 2019'a kadar olan dönemdeki aylık verileri kullanarak incelemektedir. Uzun dönemli bağ, her ikisi de yapısal kırılmaları dikkate alan eşbütünleşme testi ve dinamik eşbütünleşme regresyonu (Dinamik OLS) ile gösterilmektedir. Sonuçlar, uzun dönemli ilişkilerin IND'den TSI'ye, IND'den DJT'ye ve DJT ile TSI arasında iki yönlü testlerle kanıtlandığını göstermektedir. Daha da önemlisi, Granger-nedensellik ilişkisi ileri, yuvarlanan ve özyinelemeli pencere algoritmalarıyla ortaya çıkar. Bu, algoritmaları takip ederek yeni ekonometrik metodolojiyi kullanarak ulaşım ölçülerindeki nedensellik bağlarını araştıran literatürdeki ilk çalışmadır. Yuvarlanan ve özyinelemeli nedensellik sonuçları, IND ile TSI, IND ve DJT ve TSI ve DJT arasındaki iki yönlü nedenselliği tespit eder. Ardından ulaşım kuruluşlarının, ulaşım sektörünün finansal yapısını modifiye etmesi ve durgunluk dönemlerinden önce, sırasında ve sonrasında ulaşım hareketliliği içinde endüstri yapılarını yeniden düzenlemeye yoğunlaşması gerektiği yönünde bazı öneriler getirmekteyiz.

Anahtar Kelimeler: Ulaşım hizmetleri endeksi, Dow Jones ulaşım endeksi, endüstriyel üretim endeksi, özyinelemeli nedensellik

Makale Türü: Araştırma

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Introduction

The versatility of economic activities is a phenomenon interacting with the financial market that is quite complicated and worthwhile to determine. The identification of this bridge and the intersection points are crucial. Therefore, within the scope of this study, we choose the transportation sector to enhance the sanctity ascribed to the new outlook on the relationship. This is noticeable; among other factors, linking the real economy and financial market through mobility in transportation, which may represent dynamic and veiled cooperation, can provide policy implications to relevant public and private agencies. Economic activities are linked to the transportation sector directly and indirectly regarding both ease of economic development and breadth of industrial potential. Transportation sector, which is essential for economic activities, might also be acting as a crucial sector for financial activities directly or indirectly. Clearly, from this perspective, there is a need to examine transportation's role in the interaction between economic activities and the financial market. To capture this aspect, one should specify how these connections are acting.

This paper aims to provide empirical evidence to reveal the causal linkages among transportation, financial market, and economic activity. Firstly, the Transportation Services Index (TSI, hereafter) has prevailed as a proxy measure of transportation. The Bureau of Transportation Statistics (BTS) from the US Department of Transportation (DOT) creates TSI that covers available data on freight traffic, passenger travel, and the combination of both to yield a monthly measure of transportation services output. TSI, which measures freight and passengers' movement, is selected in the context of an eligible form of transportation mobility.

Transportation is considered an essential driver of economies, especially for growth and development via freight and passengers' movement. In other words, transportation is mainly to provide the accessibility of goods and services that contributes to economic improvement. As such, enhanced transportation has several potential economic effects. Because transportation can be modeled primarily as a function of cost and time, expanding, and collapsing options. From this point forth, it facilitates economies' face value by making the movement of goods and services more accessible, better, and faster. This is a fact that is shaping the demand for both passenger and freight transportation.

The demand for any goods and services is determined by prices, income, wealth, future expectations, tastes, and preferences. In this manner, the demand for transportation must also be related to these determinants. Income represents the flow of economic activities, and therefore researchers refer primarily. On the other hand, wealth is the social value of an economy's stock of capital assets, comprising produced capital, human capital, and natural capital (Dasgupta, 2012). The crucial point of departure for using wealth and income together indicates an accumulated and dynamic influence. Income may reflect a power that has reached, but wealth is always an access point to power in many forms (O'Donnell, 1994). Income and wealth concentration are inversely impressed with how technological progress shapes wealth distribution, accounting for wealth mobility fluctuation (Edlund and Kopczuk, 2009). In compliance with the Vickerman (1996), technology and transportation connection reinforce input-output transition, where the importance of demand concerning its economic structure through input-output relationship. Income and wealth can affiliate to demand, which has dynamic interference with accessibility-mobility interplay by transportation.

Second, the Industrial Production Index (IND, hereafter) represents the economic activity in our analyses. Board of Governors of the Federal Reserve System composes this index as an economic indicator that measures real output for all facilities located in the United States. IND is compiled monthly to bring attention to short-term industrial production changes, measuring movements in production output, and highlighting structural developments in the economy. In other words, IND is a set of actions modifying business cycles, and, therefore, improved transportation, which is deemed a structural feature of economies (Dasgupta, 1999),

produces substantial economic benefits, and facilitates economic performance (see e.g., Bose and Haque, 2005; Easterly and Rebelo, 1993; Melo et al., 2013). Banister and Berechman (2001) attributed a complementary role in the transportation sector, which is also assigned in conjunction with positive economic externalities and investment decisions.

Prima facie, transportation is referred to as overcome space and is considered a substitutable factor to overcome spatial separation (Vickerman, 2008). Besides, communities are connected via transportation choices related to spatial growth, which also means accessibility that develops transportation availability, travel time, safety, and convenience (Karou and Hull, 2014). Moreover, transportation is an essential factor that facilitates the accessibility and increases the productivity of inputs by reducing costs for the most part (Moses, 1958), for instance, international trade (Krugman, 1991). Transportation usage across industries is considered an efficient mechanism for its sectoral differences in the output and productivity effect within industry sectors (Melo et al., 2013). Furthermore, transportation possesses positive spillover effects and network properties that influence economic activities in local, regional, national, and even international estimates (see e.g., Hulten and Schwab, 1984; Munnell, 1992).

Transportation also plays a significant role in the location choice of economic activities. The optimal location decision depends on the least-cost choice, either being close to inputs or market, which are always contestable within firms (Mejia-Dorantes et al., 2012). The linkage between transportation and input selection can set a necessary procedure that culminates in product composition, supply chain, and potential market (McCann, 1995). Another fundamental contribution of transportation terms as agglomeration effects (see e.g., Graham, 2007; Venables, 2007) is to question whether such a relationship would hold in employment and income generation. While the significance of transportation for the sectoral structure is thus well organized, there has been a broad empirical attempt to analyze the positive impression on employment (see e.g., Brueckner, 2003; Button et al., 1999; Button and Taylor, 2000; Goetz, 1992). More specifically, the mobility of production factors is likely to be associated with spillover effects regarding economic benefits across locations (see e.g., Boarnet, 1996; Duran-Fernandez and Santos, 2014).

There is substantial literature on examining the interactions between transportation mobility and economic measures by using causality analysis (see e.g., Beyzatlar et al., 2014; Brugnoli et al., 2018; Button and Yuan, 2013; Jiwattanakulpaisarn et al., 2010; Maparu and Mazumder, 2017; Mukkala and Tervo, 2013; Pacheco and Fernandes, 2017; Saidi et al., 2018; Van De Vijver et al., 2014). This method has become very important to policymakers and other stakeholders to comprehend better whether it is unidirectional or bidirectional or indeed no causal relation that could differ depending on the period and the geography under investigation. To better understand which way the causality relations run can, for example, guide policymakers in answering whether it is better value to support transportation measures (which may then boost economic measures) or economic measures directly (which may then boost transportation measures).

Empirical studies assess the economic impact of passenger and freight movement on income, using GDP or GDP per capita, which are the most critical indicators of economies; there is considerable documentation on the Granger-causality relationship between income and transportation measures[3]. As expected, mixed results were obtained for different country groups at different levels of aggregation and time-period. While a group of studies found the direction of causality running from income to transportation movement (see e.g., Fernandes and Pacheco, 2010; Mukkala and Tervo, 2013; Hakim and Merkert, 2016), another group found the opposite direction of causality running from transportation movement to income (see e.g., Hu et al., 2015; Tong and Yu, 2018). Finally, the remaining studies found evidence that the causal

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[3]Our review excludes Granger-causality studies on transportation infrastructure, as it is a stock variable. See the comprehensive literature review in Maparu and Mazumder (2017).

relationship between income and transportation movement is dominantly bidirectional (see e.g., Baker et al., 2015; Beyzatlar et al., 2014; Chang and Chang, 2009; Hu et al., 2015; Pradhan and Bagchi, 2013; Tong and Yu, 2018). Of the studies reviewed, Yao (2005) and Sharif et al. (2019) observed the empirical linkage between industrial production and transportation services index for the US by using causality analysis 1979-2004 and quantile-on-quantile approach for the period 2000-2017, respectively. According to Yao (2005), findings show unidirectional causality running from industrial production to transportation services index by using monthly data. The latter research, Sharif et al. (2019), implies that the effect of the transportation services index is positive but weak on industrial production, whereas industrial production is also positive and strong. However, both studies reflect controversial results, which should be tested with a more accurate econometric methodology for the US.

Lastly, the Dow Jones Transportation Average Index (DJT, hereafter) echoes for the financial market. DJT stands for representing a 20-stock, price-weighted index representing the stock performance of public US corporations operating in the transportation industry. We preferred this index because it reflects the financial side of transportation, which is our benchmark to observe the interconnection between financial development and economic activity. The present paper is also close in spirit to that of Lahiri and Yao (2006). This study presents DJT as one of the leading indicators related to transportation and economy wide as well.

Many studies addressing the relations between financial markets and economic activities (such as GDP, GNP, trade, and industrial production) for many decades (see e.g., Barro, 1990; Bencivenga et al., 1996; Chen et al., 1986; Fama, 1981, 1990; Geske and Roll, 1983; Kaul, 1987; Levine and Zervos, 1998). In spite, however, of many viewpoints, none of them developed an idea of the extent of transportation. As we consider many of those left behind, it might become clearer by providing how DJT exploits a proxy measure for transportation in financial markets and how the financial side of the transportation is related to industrial production (i.e., the output side of the economy) through transportation mobility.

The frame of the concept we have been able to piece together thus far concerns trilateral nexus offset by the prominence assigned to transportation. (i) TSI denotes the movement as a combined index, including both freight and passenger mobility; (ii) DJT represents the corporate side, as a financial index comprises income and wealth; (iii) IND is covering the real output as a significant economic indicator concerning transportation. The inclusion of different angles to empirical analyses could be an effectual bridge when considering the interaction towards transportation demand provided by income and wealth accumulation through the financial market. Whether due to income or wealth, the demand for transportation changed into freight and passenger movement. In this manner, the evidence of causality should also be determined and justified among transportation and financial dimensions as reasonable as economic measures. Additionally, we examine the inter-market linkages between the financial market and the real sector over transportation and their contributions to transportation mobility. Lastly, the involvement of financial features of transportation could implement early warning signals from the financial market, which is preliminary affected in the pre-crisis period. This can be important to take an appropriate course of actions to prevent the spread of crisis and losses from externalities in the transportation sector and the real economy as early as possible. Therefore, effective crisis management and necessary regulations can be implemented through the coordination of the movement of people, and the mobility of goods and services.

Eventually, our contributions to the literature are two-folded. In the first place, this research suggested showing the causal relationship and the direction of causation empirically between (i) TSI and DJT, (ii) TSI and IND, and (iii) DJT and IND. To understand better which way the causalities run can, for example, guide policymakers in deciding which policy actions could be applied to support and need to be a part of their strategies. Second, the novelty in this study is that we employ a novel method to determine causal relations based on a recursive

evolving window algorithm, which provides better performance for detecting and dating causal changes than conventional methods. In contrast to the considerable literature documenting the relationship between economic, financial, and transportation measures, no effort has been devoted to this point to date.

The remainder of the article has organized as follows: Section 1 details the methodology; Section 2 presents data and empirical results; the last section provides conclusion remarks and recommendations.

1. Methodology

1.1. Cointegration Test and Dynamic OLS

Maki (2012) proposes the following regression model to test cointegration allowing for multiple structural breaks:

$$y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} + \beta' x_t + \sum_{i=1}^{k} \beta'_i x_t D_{i,t} + u_t \tag{1}$$

where $t = 1,2,\ldots,T$. y_t (dependent) and $x_t = (x_{1t},\ldots,x_{mt})'$ (regressors) indicate observable integrated of order one (I(1)) variables, and u_t is the equilibrium error. $D_{i,t}$ takes the value of 1 if $t > T_{Bi}$ $(i = 1,\ldots,k)$ and of 0 otherwise, where k is the maximum number of breaks and T_{Bi} indicates the time of the break. The model captures the potential changes in the level (μ), trend (γ), and regressors (x). The test with the null hypothesis of no cointegration against the alternative hypothesis of cointegration with i breaks (i≤k) is estimated via the procedure described in Maki (2012). We compute the t-statistics to test for a unit root in the residuals obtained from the estimated model, for all possible periods of the break. Let the set of all possible partitions and the t-statistics be represented by T_i^a and τ_ρ^i, respectively. The ith breakpoint ($\hat{b}p_i$) is chosen by minimizing the sum of squared residuals (SSR) for the estimated model; the breakpoint i can be indicated as $\hat{b}p_i = \arg \min_{T_i^a} SSR_i$. Finally, we adopt τ_{min}^k as the test statistic, that is, the minimum t-statistic over the set $\tau_\rho^k = \tau_1 \cup \tau_2 \cup \ldots \cup \tau_k$. The cointegration test proposed by Maki (2012) perform as well as the previously developed tests allowing structural breaks in the data, Gregory and Hansen (1996) and Hatemi-J (2008), which allow one and two breaks in the cointegration vector, respectively. However, the Maki (2012) cointegration test based on Bai and Perron (1998, 2003) and Kapetanios (2005) performs better when there are more than three breaks or persistent Markov switching shifts in the cointegration vector (Maki, 2012: 2015). Applying such a cointegration test with a better empirical size when the maximum number of breaks increases (Maki, 2012: 2014) allows us to reach accurate results, considering this paper analyzes an extended sample period.

Next, we estimate the following cointegrating regression using the dynamic ordinary least squares (DOLS) algorithm developed by Stock and Watson (1993) to estimate the long-run relationships among time series:

$$y_t = \lambda^d x + \sum_{-n}^{n} \Delta x_{t-1} + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} + \sum_{i=1}^{k} \beta'_i x_t D_{i,t} + u_t \tag{2}$$

where λ^d is the vector of long-run coefficients of x; $D_{i,t}$ represents the break(s) in the cointegration vector determined by the cointegration test, taking the value of 1 if $t > T_{Bi}$ $(i = 1, I, k)$ and of 0 otherwise. We determine the lag and lead in the first difference of regressors based on the Schwarz Information Criterion (BIC).

1.2. Granger Causality

Toda and Yamamoto (1995) suggest estimating the following VAR(p+d) model, where d is the maximum integration degree of time-series:

$$y_t = c + B_1 y_{t-1} + \cdots + B_p y_{t-p} + \cdots + B_{p+d} y_{t-(p+d)} + \varepsilon_t. \tag{3}$$

where yt is a vector of k variables, c is a vector of intercepts, ε_t is a vector of error terms, and B is the matrix of parameters. By imposing zero restriction on the first p parameters in (1), we obtain Wald statistics following χ^2 distribution, with p degrees of freedom, under the null hypothesis of Granger non-causality against the alternative hypothesis of Granger causality.

The above-described Granger causality test is sensitive to the period of estimation; (Shi et al. (2018) propose a novel recursive evolving window algorithm for detecting changes in causal relationships. The recursive evolving window algorithm is an extension of both the forward expanding window algorithm by Thoma (1994) and the rolling window algorithm by Swanson (1998). Different from the conventional Granger causality test, we estimate W for each subsample regression in the recursive evolving window algorithm and estimate sup W (SW$_r$) as follows:

$$SW_r(r_0) = \sup_{(r_1,r_2)\in\Lambda_0, r_2=r} \{W_{r_2}(r_1)\} \tag{4}$$

where $\Lambda_0 = \{(r_1, r_2): 0 < r_0 + r_1 \leq r_2 \leq 1, \text{and} 0 \leq r_1 \leq 1 - r_0\}$, r is the observation of interest, r0 is the minimum window size, r1 and r2 are the starting and terminal points of the sequence of regressions, respectively. Origination (re) and termination (rf) dates in the causal relationship are calculated according to the following crossing time equations:

$$\hat{r}_e = \inf_{r\in[r_0,1]} \{r: SW_r(r_0) > scv\} \tag{5}$$

$$\hat{r}_f = \inf_{r\in[\hat{r}_e,1]} \{r: SW_r(r_0) < scv\} \tag{6}$$

where *scv* is the sequence of the bootstrapped critical values of the *SW$_r$* statistics.

2. Data and Empirical Results

We use the Transportation Services Index (TSI), Industrial Production Index (IND), and Dow Jones Transportation Average (DJT) series. The monthly data are obtained from various sources, including Federal Reserve Economic Data (FRED) of St. Louis Fed (fred.stlouisfed.org) and the FactSet. The sample period covers January 20–0 - March 2019. The availability of TSI on FRED dictates the choice of the starting point of the sample period.

Figure 1. TSI, IND, and DJT, 2000-2019, US monthly data
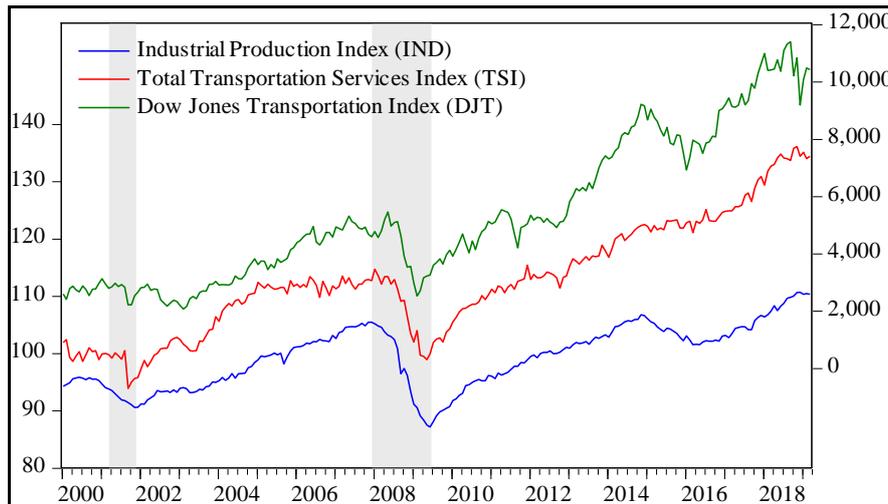
Note: The shaded areas denote the NBER-based recession dates in the US. IND and TSI are scaled on the left axis, and DJT is scaled on the right axis.

Figure 1 shows the movements of the series DJT, IND, and TSI over time. All series are moving together, even during recessions, in a nonstationary fashion. The graphical

representation shows foundational evidence for a long-run relationship. The shaded areas in the figure show recession periods in the US. The first shaded area corresponds to the bursting of the dot-com bubble, as well as the slowing GDP growth rate. The second and larger shaded area denotes the Great Recession, triggered by the bursting of the housing bubble, spilled over the industrialized economies. In the subsequent analyses, the data are transformed into a natural logarithm form. We report the descriptive statistics for the natural log-levels of the series in Table 1.

Table 1. Descriptive statistics, log levels

	IND	TSI	DJT
Mean	4.597	4.720	8.478
SD	0.055	0.087	0.466
Max	4.706	4.913	9.340
Min	4.467	4.541	7.625
Kurtosis	-0.837	-0.589	-1.091
Skewness	-0.183	0.240	0.126

We check the time series' integration properties using the unit root test developed by (Lee and Strazicich, 2003). The results obtained from the unit root test with structural breaks are reported in Table 2. The null hypothesis of the unit root test is that time series contains a unit root; thus, they are not stationary over time. We cannot reject the null hypothesis of unit root for the log-level of the time series; however, we reject the null hypothesis for their first differences at the 1% level. These results suggest that the time series are integrated of order one (I(1)), and the maximum order of integration is one (1). The breaks points determined by the unit root test are clustered around significant socio-economic and political events, such as the Iraq War, which started in March 2003, the economic effects of natural disasters in 2005, the Great Recession of 2008/09 in the US due to mortgage delinquencies, the collapse in oil prices, surge in the US stock markets, and sharp appreciation of the US Dollar against the major currencies in late 2014.

Table 2. Lee and Strazicich (2003) unit root tests

	LM	TB1	TB2	Lag
Level (Log)				
IND	-5.541	Sep-05	Oct-08	6
TSI	-5.140	May-03	Nov-08	9
DJT	-4.572	May-05	Nov-08	12
First Differences (Δlog)				
ΔIND	-8.052 ***	Jul-05	Aug-08	6
ΔTSI	-13.955 ***	Jun-08	Oct-09	1
ΔDJT	-12.295 ***	Jan-08	Oct-08	1

Note: LM is the test statistics, testing the null hypothesis of the unit root test is that time-series has a unit root. *** denotes statistical significance at the 1% level.

After finding that the time-series are integrated at the same order (I(1)), we check whether all possible pairs of the time-series are cointegrated, which implies they track each other in the long-run. We apply Maki's (2012) cointegration test, which considers up to five (5) unknown structural breaks determined endogenously. The null hypothesis of the cointegration test is no cointegration between the time-series. Table 3 reports the results of the cointegration test. We reject the null hypothesis of no cointegration between IND and TSI at the 10% level, only when the dependent variable is TSI, implying a long-run relationship between IND and TSI. For IND and DJT, we reject the null hypothesis of no cointegration at the 1% level, only when the dependent variable is DJT, indicating a long-run relationship between them. For TSI and DJT, we also reject the null hypothesis of no cointegration at the 10% level or better,

confirming long-run co-movement among the series. The Maki (2012) test detects two structural breaks in the cointegrating relationship between IND and TSI and five structural breaks in the other two cointegrating pairs, IND-DJT and TSI-DJT[4].

As discussed in the previous section, applying the Maki (2012) cointegration test leads us to reach more accurate results than employing conventional cointegration tests, as well as Gregory Hansen (1996) and Hatemi-J (2008) tests, particularly for the cointegrating relationships, IND-DJT and TSI-DJT, of which cointegrating vectors have more than three breaks. We might not have rejected the null of no cointegration if we had employed the cointegration tests that do not consider more than three breaks or persistent Markov switching process, indicating the usefulness and appropriateness of the Maki (2012) cointegration test in this paper.

The breakpoints in the cointegrating vector are accumulated around significant events, similar to those captured by the unit root test. Additionally, the cointegration test detects breaks in late 2012 and 2013, which may be linked to the fourth phase of the quantitative easing (Q4) by the Federal Reserve, which kept interest rates low, aiming to stimulate economic growth. Furthermore, in 2013, the US economy grew significantly, the GDP growth rose for four straight quarters, owing to the strengthening housing sector.

Table 3. Maki (2012) Cointegration Test Results

Dependent	τ	TB1	TB2	TB3	TB4	TB5
Panel a. IND ↔ TSI						
IND	-4.720	Jun-01	Aug-07	Aug-08	Oct-09	-
TSI	-7.144 *	May-08	Dec-12	-	-	-
Panel b. IND ↔ DJT						
IND	-5.495	May-08	Jul-09	Sep-11	-	-
DJT	-9.751 ***	Mar-02	Dec-04	Aug-06	Apr-08	Dec-12
Panel c. TSI ↔ DJT						
TSI	-8.502 **	Nov-04	May-08	Mar-10	Mar-13	Jan-16
DJT	-7.295 *	Nov-01	Jan-03	Jun-05	Apr-08	Sep-13

Note: *, **, and *** denote rejection of null hypothesis at 10%, 5%, and 1% statistical significance levels, respectively. The null hypothesis of Maki (2012) test is that the time series are not cointegrated.

Table 4 reports the results of the Dynamic OLS regressions with breaks, applied to cointegrated pairs, TSI-IND, DJT-IND, TSI-DJT. The second column of Table 4 shows that the parameter estimates for the regressors have positive signs, and they are statistically significant at the 1% level, suggesting that IND has a positive impact on both TSI and DJT in the long-run and that TSI and DJT affect each other positively in the long-run. The time dummy variables interacting with the intercept, regressors, and linear trend are generally significant at conventional levels, indicating that parameter estimates tend to change over time due to the structural breaks.

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[4]One should not expect that the number and time of breaks detected by the unit root test are the same as those detected by the cointegration since the former detects a maximum of two breaks where the test statistics is minimized for a single series, while the latter tests null of no cointegration, allowing for an unknown number of breaks in the combination of series, the residuals.

Table 4. Dynamic OLS with breaks

	TSI=f(IND)	DJT=f(IND)	TSI=f(DJT)	DJT=f(TSI)
x	0.536 *** (0.089)	7.239 *** (1.985)	0.136 *** (0.023)	5.310 *** (0.950)
μ	2.154 *** (0.403)	-25.154 *** (9.064)	3.499 *** (0.182)	-16.571 *** (4.385)
γ	0.001 *** (0.000)	0.017 *** (0.005)	0.002 *** (0.000)	0.008 ** (0.003)
DTB1	-1.426 *** (0.458)	12.228 (13.469)	1.077 *** (0.243)	2.340 (12.272)
DTB2	-0.465 (0.447)	-1.871 (10.256)	0.004 (0.306)	25.482 *** (5.046)
DTB3	-	19.722 (12.587)	0.346 (0.249)	12.980 * (7.736)
DTB4	-	15.484 * (8.820)	0.384 * (0.206)	4.745 (4.232)
DTB5	-	17.798 * (9.496)	0.526 ** (0.253)	9.128 ** (4.339)
γ * DTB1	-0.001 *** (0.000)	-0.014 ** (0.006)	-0.002 *** (0.000)	-0.054 *** (0.017)
γ * DTB2	0.001 *** (0.000)	-0.014 ** (0.006)	-0.004 *** (0.001)	0.013 *** (0.005)
γ * DTB3	-	-0.017 *** (0.006)	0.000 (0.000)	-0.001 (0.004)
γ * DTB4	-	-0.018 *** (0.005)	-0.001 *** (0.000)	-0.008 ** (0.003)
γ * DTB5	-	-0.013 *** (0.005)	0.001 *** (0.000)	-0.009 *** (0.004)
x * DTB1	0.323 *** (0.103)	-2.692 (2.982)	-0.120 *** (0.031)	-0.232 (2.760)
x * DTB2	0.071 (0.099)	0.380 (2.256)	0.028 (0.033)	-5.738 *** (1.108)
x * DTB3	-	-4.257 (2.786)	-0.055 * (0.032)	-2.875 * (1.652)
x * DTB4	-	-3.263 * (1.929)	-0.055 ** (0.027)	-0.978 (0.917)
x * DTB5	-	-3.909 * (2.078)	-0.111 *** (0.034)	-1.829 * (0.946)

Note: The numbers in parentheses are standard errors. 0.000 indicates less than 0.0005. μ is intercept, γ is time trend, and DTB(.) stands for time of structural break in the cointegration vector. *, **, and *** denote rejection of null hypothesis at 10%, 5%, and 1% statistical significance levels, respectively.. The lead and lag lengths in the models are determined by BIC.

Next, we analyze the causal relationship between the pairs by conducting (Shi et al., 201')'s Granger causality testing framework that detects and dates Granger causality episodes following the recursive evolving window algorithm. We compare the results obtained from the recursive evolving window algorithm to those obtained from both the forward expanding window (Thoma, 1994) and rolling window (Swanson, 1998) algorithms. Figures 2 to 4 illustrate the Granger causality linkages between the pairs, I–D - TSI, I–D - DJT, T–I - DJT, respectively, reporting the MWald test statistics and 90% critical value sequences. The three rows of the figures show the results of Granger causality following the forward expanding, rolling window, and recursive evolving window algorithms, respectively. We reject the null hypothesis of no causality when the MWald test statistics exceed the 90% critical value sequence. The shaded areas in the figures show the NBER-based recession dates, pointing out the Great Recession between December 2007 and June 2009.

Figure 2 illustrates the results for the Granger causality linkages between IND and TSI; the first and second columns of the figure show the results for testing Granger causality from IND to TSI and from TSI to IND, respectively. Based on the results obtained from the forward expanding window algorithm, we cannot reject the null hypothesis of no causality running from IND to TSI as the MWald statistics do not exceed the 90% critical value sequence over the sample period. However, both the rolling and recursive evolving window algorithms detect episodes of Granger causality from IP to TSI at the 10% level, or better. The rolling window detects the episodes between October 2010 and July 2011. The recursive evolving window algorithm detects similar episodes to those detected by the rolling window algorithm; first, the MWald statistics exceeded the critical value sequence in October 2008; the second episode lasts 67 months starting in October 2010 and terminating in April 2016. For the Granger causality running from TSI to IND, the forward expanding window algorithm detects two main episodes at the 10% level, or better; the first last 82 months, starting in October 2010 and terminating in July 2007; and the second lasts five months between November 2018 and March 2019. The rolling window algorithm detects several episodes of Granger causality at the 10% level, or better; the first occurs at the beginning of the sample period in April 2005; the others last for a total of 63 months between April 2010 and June 2015. The recursive evolving window

algorithm also detects similar episodes as the other algorithms; however, the duration of the episodes is slightly longer, starting earlier and/or ending later. The information transmission between IND and TSI emerges after the Great Recession, during which we do not evidence any bi-directional Granger causality between the series.

Figure 2. Granger causality between IND and TSI
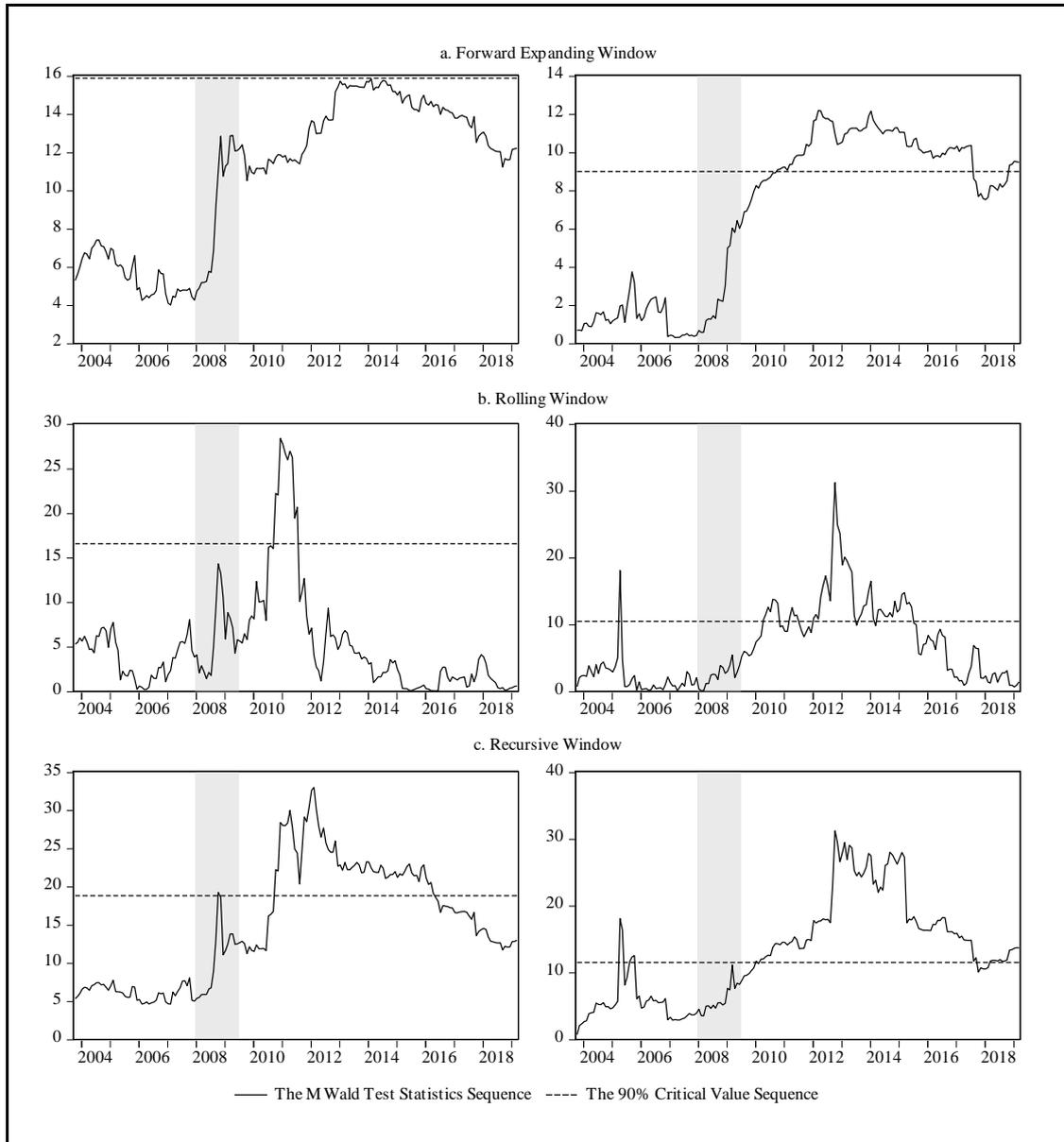
a. Forward Expanding Window

b. Rolling Window

c. Recursive Window

The M Wald Test Statistics Sequence   ---- The 90% Critical Value Sequence

Note: The three rows report the results based on the forward expanding window, rolling window, and recursive window algorithms, respectively. The left (right) column reports the results of causality tests running from IND (TSI) to TSI (IND). The shaded area indicates NBER-based recession dates. The solid line is the MWald test statistics sequence, whereas the dashed line is the 90% critical value sequence.

Figure 3. Granger causality between IND and DJT
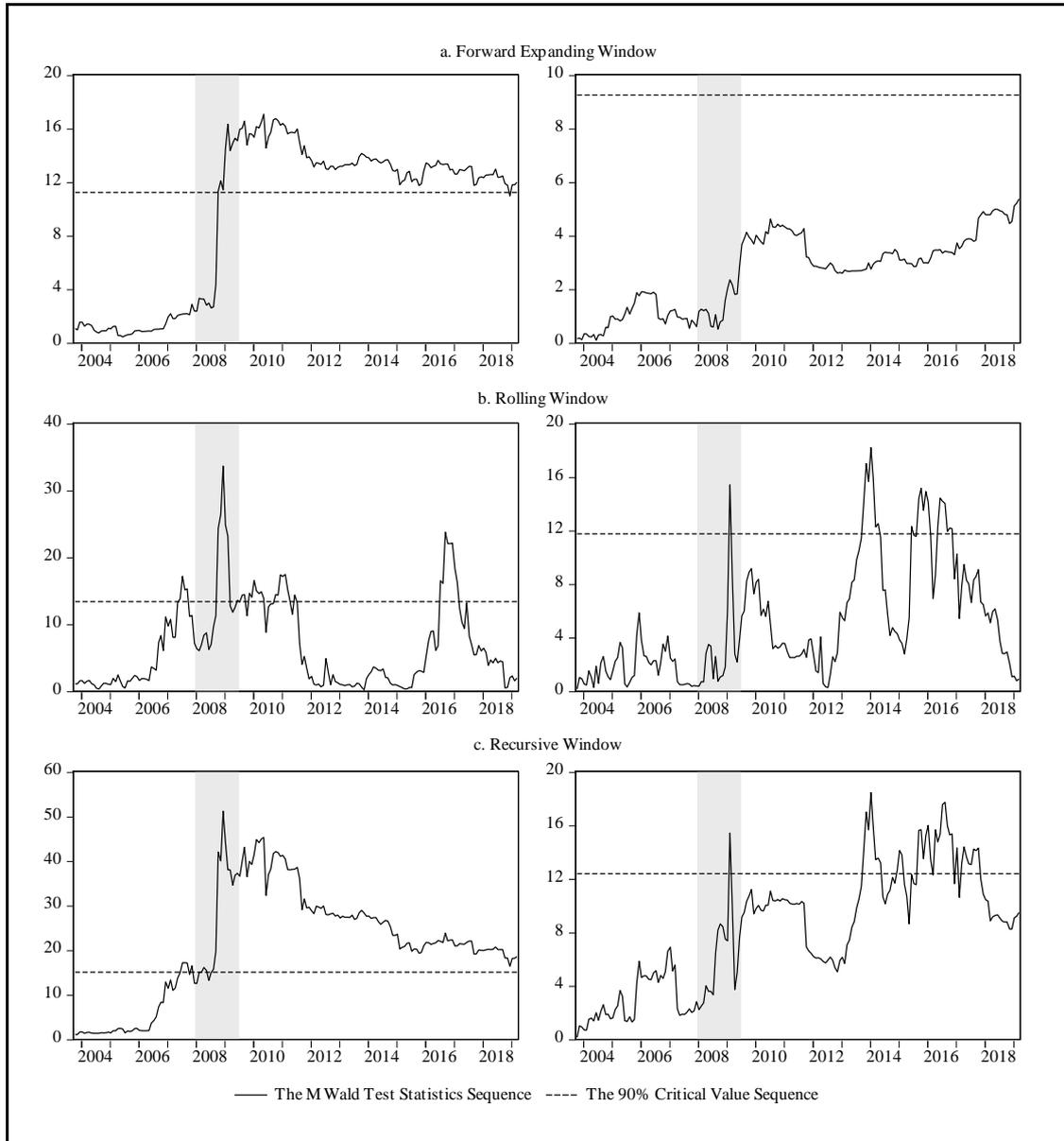
Note: The three rows report the results based on the forward expanding window, rolling window, and recursive window algorithms, respectively. The left (right) column reports the results of causality tests running from IND (DJT) to DJT (IND). The shaded area indicates NBER-based recession dates. The solid line is the MWald test statistics sequence, whereas the dashed line is the 90% critical value sequence.

Figure 3 illustrates the results for the Granger causality linkages between IND and DJT; the first and second columns of the figure show the results for testing Granger causality from IND to DJT and from DJT to IND, respectively. The forward expanding window algorithm detects Granger causality from IND to DJT at the 10% level, or better, between October 2008 and March 2019. The rolling window algorithm detects three main episodes of Granger causality from IND to DJT at the 10% level, or better, around the Great Recession period; the first lasts four months between June 2007 and September 2007; the second occurs between October 2008 and June 2009; the third is detected between August 2009 and June 2011; and the fourth lasts eight months, beginning in July 2016 and ending in February 2017. The recursive evolving window algorithm detects two episodes of Granger causality from IND to DJT at the

10% level, or better; the first occurs between July 2007 and May 2008; and the second starting in the mid of the Great Recession and continues until the end of the sample period, lasting 128 months. We evidence significant interaction between IND and DJT during the Great Recession; the bi-directional causality between the variables is found to be significant in the later period of the sample, especially between 2014 and 2017.

Figure 4. Granger causality between TSI and DJT
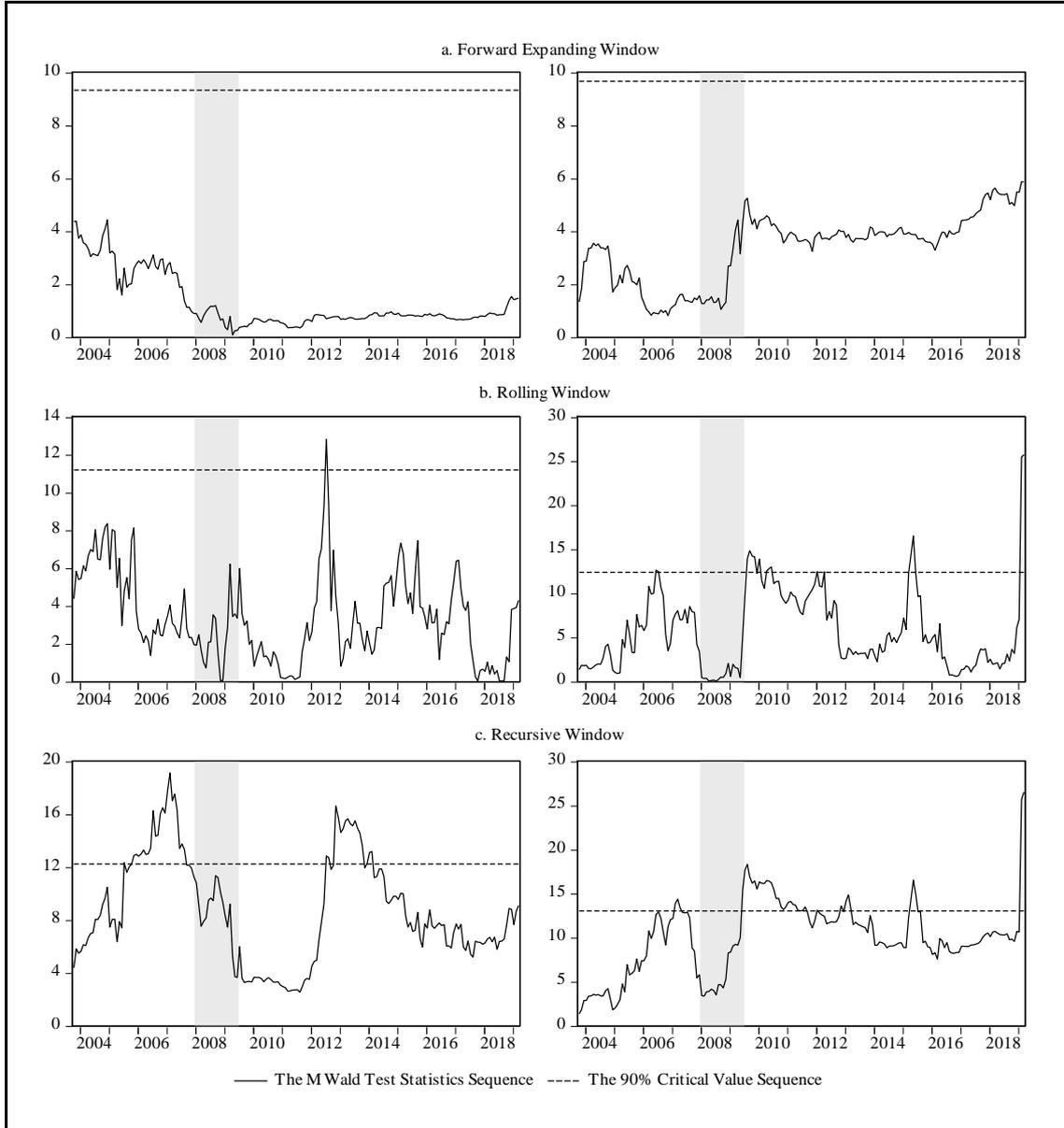
Note: The three rows report the results based on the forward expanding window, rolling window, and recursive window algorithms, respectively. The left (right) column reports the results of causality tests running from TSI (DJT) to DJT (TSI). The shaded area indicates NBER-based recession dates. The solid line is the MWald test statistics sequence, whereas the dashed line is the 90% critical value sequence.

Figure 4 illustrates the results for the Granger causality linkages between TSI and DJT; the first and second columns of the figure show the results for testing Granger causality from TSI to DJT and from DJT to TSI, respectively. The forward expanding window algorithm suggests not rejecting the null hypothesis of no causality between TSI and DJT since the

MWald test statistics are always below the 90% critical value sequence. The rolling window algorithm detects one episode of Granger causality from TSI to DJT at the 10% level, or better, lasting only one month, July 2012.

The recursive evolving window algorithm detects two main episodes of Granger causality from TSI to DJT at the 10% level, or better; the first emerges before the Great Recession, between July 2005 and August 2007; the second occurs between July 2012 and February 2014. For the Granger causality from DJT to TSI, the rolling window algorithm detects short-lived episodes of Granger causality at the 10% level, or better; the first occurs before the Great Recession lasting two months in June and July of 2006; the second emerges after the Great Recession, between August 2009 and June 2010; the third occurs in January and April of 2012; the fourth is between April and May of 2015; the fifth is detected in the last two months of the sample period. The recursive evolving window algorithm detects significant Granger causality episodes at the 10% level, or better, similar to those detected by the rolling window algorithm; however, the duration of the episodes by the recursive window is considerably longer. The information transmission between TSI and DJT is not lasting as much as between the other pairs and does not occur during the Great Recession.

Table 5. Summary of test results

Variables	Cointegration	Granger Causality		
	Maki	Forward	Rolling	Recursive
IND & TSI	IND → TSI	IND ← TSI	IND ↔ TSI	IND ↔ TSI
IND & DJT	IND → DJT	IND → DJT	IND ↔ DJT	IND ↔ DJT
TSI & DJT	TSI ↔ DJT	IND x DJT	TSI ↔ DJT	TSI ↔ DJT

Note: The arrows show the direction of the relationship; x → y indicates that x affects y; x↔y indicates that the time series affect each other.

Table 5 summarizes the empirical results based on the cointegration and Granger causality tests, revealing the importance of considering structural breaks and modeling changes in causal relationships in a dynamic setting.

Conclusion and Recommendations

There is a vast amount of empirical studies in the literature which have concentrated on the feature of economic measures in clarifying transportation and vice versa. The novelty of this study is the introduction of the financial aspect of transportation by the Dow Jones transportation index (DJT) and using the transportation services index (TSI) as a consistent indicator of transportation mobility. Besides the financial market, the industrial production index (IND) regarding the real sector has been utilized to probe the versatile relations between these two sectors' mobility and contributions through transportation. Therefore, it is also aimed to illustrate that this trio brings a new understanding of transportation economics. These interactions are examined for the United States of America by using monthly data from January 2000 to March 2019 by using some econometric tests. In this regard, in the characterization of nexus within variables, an emphasis is set on a novel methodology, following the recursive evolving window algorithm to reveal robust estimations. This is the first study in the literature to investigate the causality relationship in transportation measures by using the novel technique, following the recursive evolving window algorithm.

The long-run relationship between variables is established via cointegration test developed in Maki (2012) and dynamic cointegrating regression (Dynamic OLS) launched by Stock and Watson (1993) that both techniques are taking structural breaks into account. The cointegration test results show that TSI and DJT are reciprocally cointegrated. In addition to that, the direction of cointegration was observed from IND, respectively, to DJT and TSI. The Dynamic OLS results suggest that IND has a positive impact on both TSI and DJT in the long-

run and that TSI and DJT affect each other in the long-run. The results are consistent with each other throughout the long-run relations.

Moreover, the Granger-causality is revealed with forward, rolling, and recursive type techniques as a continuation of the relationship between variable pairs. The forward type test results show a unidirectional causality running from TSI to IND and IND to DJT, but no causality running from TSI and DJT. However, rolling, and recursive type Granger-causality test results show a bidirectional causality between TSI and DJT, DJT and IND, TSI, and IND. Subsequently, the recursive evolving window algorithm suggests many more Granger causality episodes until the end of the sample period.

This triangular relationship between TSI, DJT, and IND makes researchers consider complex relations between finance and the real economy. On the other hand, viewing finance as part of transportation economics, like to enhance the communal structure of freight and passenger mobility to another viewpoint. These movements cover both inputs and outputs, which appear to be more important during crisis periods and both factors act as heuristics when people have insufficient time, cognitive capacity, or motivation to evaluate risks deliberately. The coronavirus disease 2019 (Covid-19) pandemic exhibits the importance of transportation in many aspects; however, efficiency and effectiveness issues are not completely sufficient. The movement of people and mobility of goods and services become more apparent during contagion because of an inadequate functioning of transportation. Access to food, education, healthcare, and even to work or house become based more on the structural aspects of transportation. Nevertheless, the idea of the value of improving accessibility may also be manageable by private and public contribution, as in the last instance, because these reforms require human capital enhancement. There are three major types of skills: cognitive, people, and motor, based on the Occupational Information Network by the US Department of Labor classification. These are thus correlative to knowledge, managing, and physical skills, respectively. Weinstein and Patrick (2019) contrives that these skills are also as substantive as education for the wealth accumulation in economies. According to their results, skills are interacting with unemployment during recessionary periods. These skills also play a significant role in how economies cope with and then recover from downturns in safe and sound conditions or not. Based on these, the allocation, compensation, and accumulation of human capital are vital for financial markets.

Furthermore, the relationship between DJT, IND, and TSI covers these job-based skills. In policy circles, the transportation institutions should modulate the transportation sector's financial structure and intensify to adjust industry structures within transportation mobility before, during, and after recessionary periods based on these skills. Therefore, policymakers and strategists could promote people-centered transportation policies, aiming to increase the labor force and businesses' productivity and competitiveness. The claim is that transportation is notable for bridging financial aspects and real economy to facilitate economic development through business cycles.

Future studies may want to consider the efficiency of transportation, in a broad sense, by using, (i) different modes of transportation such as rail, road, and maritime, (ii) transportation infrastructure, (iii) transportation capacity, and (iv) investment in transportation as relevant variables within the context of causality approach. Financial and economic indicators may also be changed with different variables for different countries. Future alternative studies might also use the same or various determinants of transportation, financial and economic indicators for an alternative time and cross-sectional dimensions as a longitudinal investigation due to the nature of the transportation. Lastly, data availability is a challenging task of transportation economics especially in accessing high-frequency data to be compatible with not only transportation data but also many other measures.

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