The direct and spillover effects of liner shipping connectivity on merchandise trade

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Abstract

Purpose – This paper aims to address the following questions: is good liner shipping connectivity a requisite for merchandise imports plus exports? What is the average of merchandise imports plus exports of the countries neighboring China? Do the merchandise imports plus exports of these countries correspond to each country's own merchandise imports plus exports or liner shipping connectivity index (LSCI)?

Design/methodology/approach – The authors spatially analyze liner shipping connectivity and merchandise imports plus exports using 2016 data and a common framework for linear regression to establish the relationship amongst a country's LSCI and its merchandise imports plus exports and between its merchandise imports plus exports and those of its neighbors. Merchandise imports plus exports of countries are not necessarily independent of each other, and countries that are contiguous may produce similar observations.

Findings – North America and Western Europe comprised clusters of countries that participated more actively in the international trading system, while Africa's countries had less international trade than average. The study identifies and quantifies the geographical ripple of transport infrastructure on merchandise trade from a national perspective. Notably, a spatially lagged term improved the model's ability to account for variations in merchandise imports plus exports across countries.

Originality/value – The spatial lag of merchandise imports plus exports can contribute to specifying the spread of merchandise imports plus exports beyond what the authors would anticipate from a country's network of liner shipping.

Keywords Liner shipping connectivity index, Merchandise trade, Spatial lag

Paper type Research paper

1. Introduction and theoretical background

The mainstay of international trade is maritime transport. It carried about 80% of all trade globally, and more than 70% of the global value was transported by sea to ports around the world (UNCTAD, 2015). Global trade relies on the shipping industry to promote economic activities between economies across different geographical regions. Liner shipping services form a global maritime transport network, which moves most of the international trade in manufactured goods. Liner shipping connectivity was a crucial determinant of global trade (Chen *et al.*, 2016; Fugazza and Hoffmann, 2017; Tovar *et al.*, 2015). According to a global survey of express carriers and freight forwarders, the United Nations Conference on Trade and Development (UNCTAD) created a liner shipping connectivity index (LSCI) (maximum value in 2004 = 100). Its aim is to measure each country's shipping connections to the network. The LSCIs of 157 economies provide an annual, comprehensive and timely account of this connectivity worldwide. Economies that exhibit a higher index are more easily able to join the global transport system for international maritime freight. The LSCI can, therefore, measure both the connection to the maritime shipping network and indicate the ability to be involved with international trade. It also reflects container shipping lines' ability to maximize revenue through market coverage. The index was generated as follows. For each country, the average is calculated for five components as follows:

(1) how many ships an economy has;

(2) how many containers those ships can carry;

(3) how large the ships are;

(4) how many services they provide; and

(5) how many companies use container ships to and from the country's ports (UNCTAD, 2016a).

Figure 1 provides a world "map" showing the LSCIs generated for 157 coastal economies and territories in 2016 (UNCTAD, 2016a). It presents a cluster of good liner shipping connectivity economies in neighboring economies, as well as clusters of economies with poor liner shipping connectivity. Economies and territories with high LSCIs are illustrated in varying shades of grey, with black indicating the highest. In 2016, LSCI, China received the highest overall score of 170.85, followed by Singapore, South Korea, Malaysia and Hong Kong. The majority of economies with good liner shipping connectivity were located around

Figure 1.
The darker shades of grey show economies with higher LSCIs

LSCI_2016
0 - 0.1
1.1 - 12
13 - 33
34 - 56
57 - 87
88 - 170.85

coastal areas, while economies with poor or no liner shipping connectivity were found in-land or were land-locked.

Containerization of trade and access to containerized transport services are important determinants of an economy's trade competitiveness. Developing economies paid 40-70% more for the international transport of their imports than developed economies (UNCTAD, 2015). Comprehending the link between economic activity and freight transport contributes to an improved understanding of the dynamics of port productivity, which is important for infrastructure planning and other strategic decisions. Although ports played a significant role in transferring economic wealth to national and international economics (Song and Yeo, 2004), port throughput is the outcome of shipping network connectivity. Several studies have identified the competitiveness or performance from an individual port's perspective (Luo and Grigalunas, 2003; Blonigen and Wilson, 2008; Pettit and Beresford, 2008; da Cruz, Ferreira and Azevedo, 2013). This, the literature provides insufficient knowledge of the relationship between imports/exports flow and shipping connectivity from a national perspective.

The standard gravity model uses the country B's global income share to determine how much of country A's exports will go to country B; therefore, economies that were physically more distant from each other have less mutual trade (Wilmsmeier and Hoffmann, 2008). Figure 2 illustrates the agglomeration of merchandise trade in 2016. The statistics derived from an official source of information about imports and exports worldwide (UNCTAD, 2016b) are the value of goods, which add or subtract from the stock of material resources of an economy by entering or leaving its territory. Economies with more international trade than average are illustrated in darker gray than economies with less than average. On both the export and import sides, large traders are China, Germany, Australia and the USA. The US was the largest trading nation in 2016, and therefore, represented one of the largest markets for liner shipping companies and their customers. An economy's liner shipping connectivity was closely related to its seaborne trade in manufactured goods (Hoffmann, 2012). In 2016, China was the largest export-oriented manufacturing economy, with a 22% share of manufacturing activity. The US was in second place, with a 17.4% share. In most developed regions around the world, the container accounts for a large portion of the maritime cargo, both exports and imports (Notteboom and Rodrigue, 2008). Clusters of economies in Western Europe and North America participated more actively in the international trading system, while Africa comprised economies with less international trade than average. Merchandise trade and liner shipping connectivity displayed spatial agglomeration.

Figure 2.
Economies with higher international trade in goods (imports and exports in millions of dollars) are shown in darker shades of greys

In this paper, we model the spatial link between merchandise trade and liner shipping connectivity using a linear regression framework. Spatial patterning provides useful information about unobserved influences and challenges the statistical methods that are found within the assumption that observations are independent of each other. The application of statistical tools gives managers important information that allows them to respond to changes in the market. Academic researchers could also use this growing body of data to develop better supported scientific studies (Pallis *et al.*, 2017). Jane and Laih (2012) developed an algorithm that is able to compute the likelihood of shipping a given quantity of goods from one place in the network to its destination for a specific cost, assuming that the network distribution of arc capacities are independent. However, the factors that enable one country to realize good liner shipping connectivity may not exist without neighboring economies having a competent infrastructure enabling good liner shipping connectivity. This paper investigates and quantifies the impact of transport infrastructure spatial spillover on merchandise trade. Direct effects are the impacts of the spatial unit on itself; that is, the effect of LSCI of economy A on the trade of economy A. Spillover effects are the effects spatial units have on other spatial units; that is, the effect of LSCI of economy A on the trade of economy B.

We hypothesize that rebound among nearby economies affects each country's international trade in goods and liner shipping connectivity. Although there was no question that trade depends heavily on logistics performance, the analytics available to analyze this dependency and to aid in optimizing decisions, particularly regarding logistics-related investments, is limited (Ratliff and Ramudhin, 2012). The literature provides insufficient knowledge of the relationship between import/export flow and shipping connectivity from the nations' perspective. The need to identify and measure factors that influence competition in the shipping industry has attracted the attention of academic researchers, industry managers and policymakers (Lee *et al.*, 2014). We aim to address the following questions: is good liner shipping connectivity a requisite for merchandise trade? What is the average of merchandise trade of the economies neighboring China? Do the merchandise trade of these economies correspond to each country's own merchandise trade or LSCI? To answer these questions, we use the heuristic statistic suggested by Gleditsch and Ward (2001), which measures spatial relationships.

The rest of this paper is organized as follows. We model the common logarithm of merchandise trade as a linear function of LSCI and then present a case study based on 2016 data that measures the spatial relationships between merchandise trade and liner shipping connectivity globally. We subsequently discuss the results and suggest ways to use the liner shipping connectivity to predict merchandise trade. In the final section, conclusions are drawn and topics are proposed for future research.

2. The liner shipping connectivity index and merchandise trade around the world

An abridged list of merchandise trade and the LSCIs of 157 economies globally in 2016 is to be found in the Appendix. The average world LSCI was 27.44. LSCIs ranged from 1.25 for the least connecting economies to 170.85 for the highest connecting economies in 2016. Some economies with more international trade than average, such as China, achieved a good LSCI, while economies with little international trade, such as Micronesia and Palau, had low LSCIs. Was there a correlation between merchandise trade and liner shipping connectivity? Noticeably, Sri Lanka and Malta achieved good LSCIs in spite of having low international trade. At the same time, some economies with lower LSCIs had fairly high merchandise trade, such as Ireland (LSCI = 11.83; merchandise trade = US$2.06E + 11).

2.1 Ordinary least square regression
The section estimated an economy's merchandise trade, given its liner shipping connectivity level, measured by its LSCI, using ordinary least squares (OLS) regression. We first considered transformations for linearizing a nonlinear regression relation when the distribution of the error terms is reasonably close to a normal distribution and the error terms have approximately constant variance. Before deciding the predictor variable transformed to $\log_{10}$ and the dependent variable transformed to $\log_e$, we have fitted several different combinations to the transformed data and examined further whether Model 1 is appropriate. We chose the logarithmic transformation of both merchandise trade and LSCI before carrying out the regression analysis. However, due to the vastly different orders of magnitude for LSCI and merchandise trade data, the power transformation on LSCI and merchandise trade was different:

$$\log_{10}\text{Merchandise Trade}_i = \beta_0 + \beta_1 \cdot \log_e\text{LSCI score}_i + \varepsilon_i \tag{1}$$

The OLS estimates of logged merchandise trade as a linear function of liner shipping connectivity are shown in Table 1. The F-test was highly significant and supported the use of the model. The positive sign of the coefficient for the LSCI indicated a positive relationship between merchandise trade and liner shipping connectivity. For instance, the model predicted that an economy with Slovenia's LSCI (31.5) in 2016 would have a total merchandise trade of US$6.33E + 10. In addition, the model predicted that South Korea with an LSCI of 112.55 would have a total merchandise trade approximately 15 times that of Slovenia (US$9.02E + 11). For most analysts, merchandise trade of US$9.02E + 11 and US$6.33E + 10 are very different. Thus, the LSCI seemed to predict merchandise trade well. The summary of the linear regression and overall fit statistics showed an adjusted R^2 of 0.6787, with $R^2 = 0.6807$, which meant that the linear regression explained 68% of the variance in the data.

Although Figure 3 shows that the estimated regression function was close in predicting the economies' actual levels of merchandise trade, the Breusch–Pagan test, used to test whether the variance of the errors from regression is dependent on the values of the independent variables, was significant at the 0.05 level. Thus, heteroskedasticity was present, reflecting the potential problem that dyadic trade observations are dependent of one another, as the exports from country A to B should be equal to the imports of country B from A. Moreover, the trade flows, from country A to B and from country A to C cannot be considered independent of one another because they share the same sender. Model 1, which assumed that the observations were independent of each other and only the LSCI mattered for merchandise trade, disregarded obvious geographical clusters. Merchandise trade and liner shipping connectivity may share spatial agglomeration, which complicated this effect. The easiest market access for goods is in economies located nearby geographically. Good liner shipping connectivity economies are clustered. The influence that one country might

Intercept	7.80245	0.14344	54.39	<2e−16
ln LSCI	0.86978	0.04784	18.18	<2e−16
N = 157				
Log-likelihood (df = 3) = −145.9554				
F = 330.5 (df₁ = 1, df₂ = 155)				<2e−16
BP = 4.5533 (df = 1)				0.03286

Table 1.
OLS estimates of logged merchandise trade as a linear function of liner shipping connectivity

exert on another could possibly produce an agglomeration of like merchandise trade. Where spatial dependence existed among merchandise trade, the error terms ε in Model 1 were now dependent on each other, and consequently, may have underestimated the standard error of β, causing incorrect hypotheses testing.

2.2 Measuring spatial correlation and association
According to Gleditsch and Ward (2001), the definition of neighboring economies means having no more than 200 km between them. The non-negative matrix W has zero diagonal elements, because no country is its own neighbor, and the weight of each raw is proportional to 1 over the total connectivity number.

The lag of merchandise trade over space is the mean merchandise trade for all the economies connected in the network. Table 2 displays the 10 lowest and the 10 highest spatial lags for the merchandise trade variable. Kiribati has the smallest merchandise trade of US\$9.60E + 07, and its neighboring economies also have small merchandise trade. Hong Kong, Korea and Canada, on the other hand, have high merchandise trade, as do all of their neighbors.
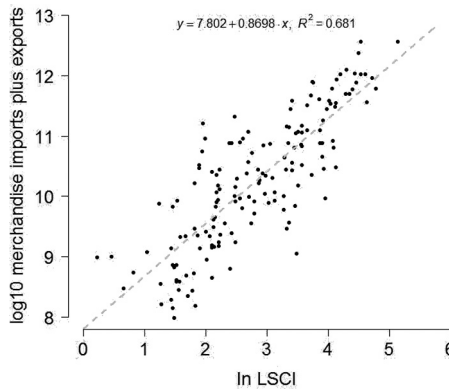

Figure 3.
Scatterplot of logged
merchandise trade
and LSCI with a
regression line

Country	Trade	Spatial Lag	Country	Trade	Spatial Lag
	Smallest			Largest	
French Polynesia	1.71E+09	9.60E+07	Pakistan	6.78E+10	1.12E+12
Marshall Islands	1.92E+08	1.96E+08	Myanmar	2.74E+10	1.20E+12
Guam	6.23E+08	2.95E+08	Bahamas	2.94E+09	1.24E+12
American Samoa	6.70E+08	3.44E+08	N. Mariana Is	1.39E+08	1.25E+12
Samoa	4.07E+08	4.76E+08	Belgium	7.71E+11	1.39E+12
Kiribati	9.60E+07	9.49E+08	Taiwan	4.97E+11	1.70E+12
Iceland	1.02E+10	1.67E+09	Canada	7.92E+11	1.85E+12
Senegal	8.12E+09	1.79E+09	Hong Kong	1.06E+12	2.10E+12
Vanuatu	4.39E+08	2.29E+09	Korea	9.02E+11	2.47E+12
Micronesia	2.95E+08	2.45E+09	BMU	9.90E+08	3.70E+12

Table 2.
The 10 economies or
territories with the
largest and the 10
economies or
territories with the
smallest spatial lags

Higher values of Moran's *I* statistic imply stronger geographical clusters, meaning that the merchandise trade of neighbors are very much alike. The easiest market access for most finished goods is in economies located geographically nearby. However, history, political friendship, colonial rules and a host of other reasons might have prevented economies from seizing this natural advantage, which has to be nurtured with a transport infrastructure and appropriate policies (Piana, 2006). Figure 4 shows the scatterplot of standardized merchandise trade compared with the spatial lag. The slope of the regression line shows the Moran's *I* for merchandise trade (0.4379), which considerably exceeds the expected value of the statistic ($-1/156$).

The "off-diagonal" points represent economies whose neighbors have enormously different merchandise trade levels, Bermuda (BMU) being the extreme. BMU (merchandise trade = US\$9.90E + 08) does not share land borders with any country and is located off the south-eastern coast of the USA, which has the highest merchandise trade (US\$3.70E + 12). The unstandardized LSCI plot is shown in Figure 5. The slope of the regression line presents the Moran's *I* for the LSCI (0.3016), which is clearly higher than the expected value of the statistic ($-1/156$). For the LSCI, the agglomeration occurs to some extent due to the fact that
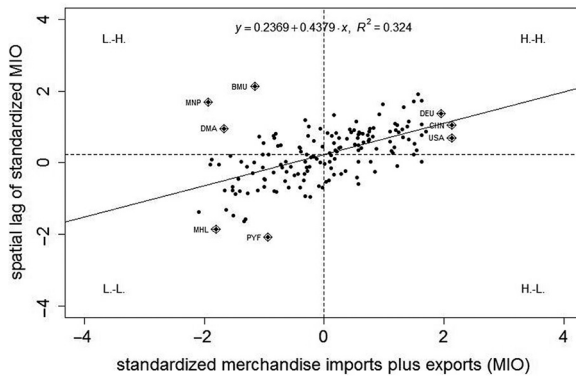
Figure 4.
Scatterplot of standardized merchandise trade against its spatial lag where Moran's *I* = 0.4379
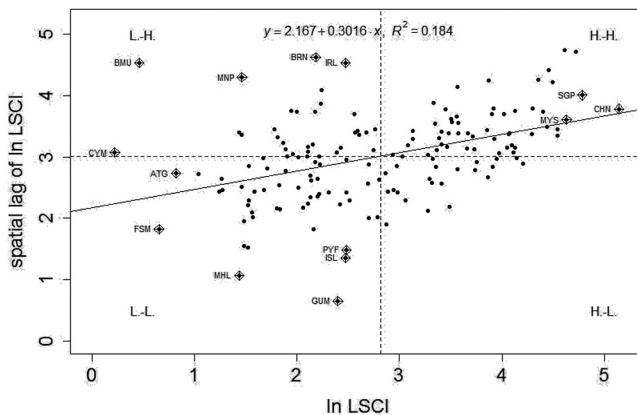

Figure 5.
A plot of ln LSCI against its spatial lag where Moran's *I* = 0.3016

ships simply pass or stop by neighboring economies before reaching their final destination. The low value of R^2 statistic may imply potential improvements of LSCI (Chen *et al.*, 2016).

The Moran's I statistic suggests extensive spatial patterning. Moran's I was 0.4379 for the common logarithm of merchandise trade and 0.3016 for the natural logarithm of the LSCI. These values suggested an unusually strong spatial pattern for both merchandise trade and LSCI.

3. Regression with the spatially lagged variables

The preliminary results demonstrate that the merchandise trade spread exhibited spatial agglomeration in such a manner that economies had a greater probability of higher merchandise trade if surrounded by other economies that had high merchandise trade. Though some of the agglomerations in merchandise trade could be attributed to spatial agglomeration in LSCI, consecutively positively related to merchandise trade, we have demonstrated that spatial agglomeration in the merchandise trade data did not completely fade away when we conditioned it on an economy's LSCI. Given that the spread of merchandise trade still exhibited spatial agglomerations even when conditioned on an economy's LSCI, we searched for feasible alternatives to integrate this spatial dependence in our regression model.

A further concern related to what sways merchandise trade, besides the relationship between an economy's LSCI and its merchandise trade. If an economy's merchandise trade seems to be related to its neighbors' merchandise trade, this tells us important information about the spread of international trade itself. It also offers an avenue for discovering possible implications of spatial relationships on outlooks for and limitations on merchandise trade. As such, a better method would be to treat spatial association as an essential characteristic of merchandise trade. The spatial association detected suggested that the expected merchandise trade of country i remarkably depended on the merchandise trade of neighboring economies j. Consequently, rather than have the expected merchandise trade of country i rely solely on the LSCI, we formulated a model in which an economy's merchandise trade was a function of both its own LSCI and the merchandise trade of its neighbors. This resulted in a spatially lagged dependent variable model with a spatial lag, as below:

$$\mathbf{Y} = \rho \mathbf{W} \mathbf{Y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon}, \ \ \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \mathbf{I}), \tag{2}$$

where $\mathbf{X}$ was a matrix of the non-stochastic regressors, $\mathbf{W}$ an exogenously given weight matrix, $\boldsymbol{\beta} = [\beta_0 \ \beta_1]^T$ and ρ the parameters to be estimated. A positive value for the parameter associated with the spatial lag ρ would imply that a country would likely have higher merchandise trade if its neighbors generally had high merchandise trade. The literature refers to this model as the spatial lag model (Anselin, 1988; Arbia, 2006). The $\hat{\beta}_1$ coefficient in the spatially lagged Model 2 differs from the coefficient computed from the OLS regression Model 1 in that we examine the LSCI effect on the merchandise trade of an economy, as well as ascertain the spatial dependence on merchandise trade or the magnitude to which country i's merchandise trade could vary because of the merchandise trade of other bordering economies j.

3.1 Regression with spatially lagged merchandise trade

Tables 1 and 3 show the OLS estimates of merchandise trade as a linear function of LSCI in 157 economies in 2016 without and with a spatial lag of merchandise trade, respectively. The F-test was highly significant and led to the acceptance of the model.

We observed a larger positive coefficient for the log of LSCI of 0.86978 in the OLS regression model without spatially lagged merchandise trade than the one with these data. On the other hand, in the spatially lagged model, the fitted coefficient for the natural log of LSCI was 0.7503. The spatially logged model summary and overall fit statistics showed an adjusted R^2 of the model of 0.7364, with $R^2 = 0.7398$.

The estimate of the spatially lagged merchandise trade was positive (0.3484) and differed significantly from 0. This suggested that an economy's merchandise trade covaried with the merchandise trade of its neighbors. The estimates represented the agglomeration of merchandise trade highlighted formerly. When the measures of the overall fit for the model that assumed independent observations in Table 1 were compared with the model with the spatially lagged merchandise trade in Table 3, it suggested that the model with the spatially lagged merchandise trade fit the data quite well. It had a better log-likelihood than the model that had assumed that the observations were independent. This strengthened our supposition that the spatial lag of merchandise trade contributes something essential to specifying the spread of merchandise trade more than what we might anticipate from an economy's liner shipping connectivity.

If we were to raise the natural logarithm of liner shipping connectivity by one unit in single country i, this would have an instant effect of β_1 on that country's merchandise trade. However, Model 2 presumed a retroactive influence between economies, in that country i's merchandise trade was also held to have an impact on its neighbors' merchandise trade. Thereby, a growth in merchandise trade that affected i's merchandise trade would affect the merchandise trade of its neighbors j. Concurrently, the neighbors' neighbors would also be impacted by the network. Almost, every country has at least one neighbor, so ultimately each one would be influenced. Notably, Model 2 included the merchandise trade of every country in the system, so that if the merchandise trade of the economies in i's network were to increase, so would the merchandise trade of i. Because of this, an external factor affecting one observation, such as China's belt and road initiative, would rebound throughout the entire network, affecting the observations, and would make its way through the system as a series of adaptations until it reached a new stable state.

Tables 1 and 3 show that the coefficient estimate of the effect of logged LSCI (0.7503) was much lower in the spatially lagged merchandise trade model than in the non-spatial OLS model (0.86978). The OLS model may have overestimated the effect of LSCI, as it did not consider the spatial agglomeration in merchandise trade and LSCIs among neighboring economies. Accordingly, the estimate was also less accurate. The spatial lag could be considered an omitted variable in the OLS model that assumed that observations were independent. In the model of spatially lagged merchandise trade, the net impact of an increase in LSCI value of country i would be realized through the feedback effect by i on its neighbor j and its impact on i itself through the spatially lagged term. The resulting effect of

Intercept	4.4777	0.5770	7.760	1.09e−12
ln LSCI	0.7503	0.0478	15.696	<2e−16
ρ	0.3484	0.0589	5.914	2.08e−08
$N = 157$				
Log-likelihood ($df = 4$) = −129.8893				
$F = 219$ ($df_1 = 2$, $df_2 = 154$)				<2.2e−16
$BP = 5.6753$ ($df = 2$)				0.05856

Table 3.
OLS with spatial lag

the increased LSCI value would influence neighboring economies and make its way through the system until a stable level was achieved.

Instead of focusing solely on the coefficient estimate for logged LSCI in a spatially lagged merchandise trade model, it is crucial to contemplate the equilibrium effect. Next, we will extrapolate the equilibrium effect of covariates in a model of spatially lagged merchandise trade by maximizing its likelihood.

3.2 Maximum likelihood estimates

This section presents the maximum likelihood estimates for the spatially lagged model of merchandise trade and compares them with the OLS estimates of the same model. The LSCI parameter was significant at the usual confidence level. Neither Jarque and Bera (1987) nor Box and Pierce's (1970) tests were significant, leading to acceptance of the two hypotheses of normality and homoscedasticity.

Table 4 shows an estimate of the coefficient for LSCI (0.7638) that is higher than the OLS estimate of the model (0.7503) and an estimate of the ρ parameter for the spatial lag of merchandise trade (0.30579) that is lower than the OLS estimate (0.3484) for the spatially lagged merchandise trade model. Our basic findings remained the same regardless of which estimation methods were used, in that including a spatially lagged merchandise trade term notably improved the model's ability to account for variations in merchandise trade across economies.

The model results indicated that each of the predictors and the spatial lag were significant. Test results suggested that the lag was a useful addition. In general, if maximum likelihood estimates seem more appropriate than OLS estimates for the spatially lagged merchandise trade, we might conjecture that the OLS estimates underestimated the coefficient for LSCI and overestimated the coefficient for the spatial lag. The Lagrange multiplier test for residual autocorrelation is the preferred test for residuals from a spatial model. The test had a value of 1.0187 with an associated probability of 0.31282, allowing a clear rejection of a remaining first-order autoregression among the residuals.

Table 4 shows that coefficients differ significantly from zero, including the spatial effect ρ, indicating that the merchandise trade of each country is related to those of its neighboring economies. The LSCI impact on merchandise trade was not as strong as the OLS results in Table 1, but were more credible. They suggested a low but still strong LSCI effect. However, the spatial lag variable appears to be salient. The coefficient estimate for the LSCI was quite large in the non-spatial OLS model compared to the corresponding coefficient for the spatially lagged merchandise trade model. The OLS model likely overestimated the immediate LSCI impact, as it did not take into account the spatial agglomeration in merchandise trade and liner shipping connectivity among neighboring economies. Therefore, the estimate was less accurate. The spatial lag could be thought of as an omitted variable in the ordinary least squares (OLS) model that assumed that observations were

Table 4. Maximum likelihood estimates of the spatial lag merchandise trade model

Intercept	4.88921	0.5620	$8.6989 < 2.2e{-}16$
ln LSCI	0.76382	0.0472	$16.1707 < 2.2e{-}16$
$\hat{\rho}$	0.30579	0.0581	$1.77e{-}07$
$N = 157$			
Log-likelihood $= -132.3228$			
AIC $= 272.65$			
LR test $= 27.265$			$1.77e{-}07$
LM test $= 1.0187$			0.31282

independent. In the spatially lagged merchandise trade model, some of the net impact of an increase in the LSCI value of country i would be realized through the feedback effect i on its neighbor j and also its impact on i itself through the spatially lagged term. The resulting impact of country i's merchandise trade would influence neighboring economies and make its way through the system until a stable level was achieved. It reflects the immediate impact rather than the long-term, net "equilibrium" effect implied by the model.

4. Direct and spillover effects

Having calculated the maximum likelihood estimates for the spatially lagged merchandise trade model, we explored the direct and spillover effects of LSCI on merchandise trade. This required considering the impact that a change in country i's LSCI would have on other economies. Because of the network matrix, this could cause a chain reaction in other economies, which would circle back to affect country i's merchandise trade via the spatially lagged item. To determine the expected value of country i's merchandise trade or the direct and spillover effects of LSCI, we considered the spatial multiplier $(\mathbf{I} - \rho \mathbf{W})^{-1}$. This multiplier would tell us how much of a change in the country i's LSCI would spill over to other economies j and, in turn, the special lag would have an impact on a country i's imports plus exports. Direct effects are the effects of the spatial unit on itself; that is, the effect of "LSCI of i-th economy" on "trade of i-th economy." Spillover effects are the effects spatial units have on other spatial units; that is, the effect of "LSCI of i-th economy" on "trade of j-th economy." To calculate the direct and spillover effects of a single difference in a few LSCI observations in the country $i(x_i)$, we multiplied a vector of Δx_i, while holding the value constant for the other economies j, by $(\mathbf{I} - \rho \mathbf{W})^{-1} \beta$. Because economies' connection to other economies varied from high to low, it seemed logical that the effect of a change in the country i's merchandise trade would also vary depending on which country was involved.

To explore changes from the direct effect, we considered the effect of a change in several economies and examined the pattern of each country's estimates. The example below shows an average direct effect of 0.7824, which is more than the immediate effect of the LSCI based on the coefficient estimate 0.7638 in Table 5. The economies' direct effects varied from a low of 0.7638 (BMU) to a high of 0.82168 (Kiribati). Assumptions about the impact of a covariate LSCI in a spatially lagged merchandise trade model should not be made until we examine the spatial multiplier and the variation that is seen across spatial units.

We chose China as an example of how the LSCI in one country affected the expected merchandise trade of others. Table 5 shows the top 10 values of $(\mathbf{I} - \rho \mathbf{W})^{-1} \beta \cdot \Delta x_i$ in China and Hong Kong.

China		Hong Kong	
Country	Impact	Country	Impact
China	0.779985	Hong Kong	0.766948
Hong Kong	0.132936	China	0.018347
Korea	0.127647	Korea	0.003003
Taiwan	0.089477	Taiwan	0.002105
Myanmar	0.064210	Myanmar	0.001510
Pakistan	0.062924	Pakistan	0.001480
Japan	0.054883	Japan	0.001291
Vietnam	0.043319	Vietnam	0.001019
Philippines	0.042964	Philippines	0.001011
India	0.036292	India	0.000854

Table 5.
Direct and spillover effects of ln LSCI for China and Hong Kong – 10 highest values

Table 4 illustrates the estimates for the spatially lagged merchandise trade model and the connectivity from **W**. We see that in Table 5, the implied equilibrium impact for China is shown as 0.779985 and for Hong Kong, it is 0.766948; both are comparable to what the model determines as the median of the equilibrium impact. Looking at values for other economies suggests that variance in China's (or Hong Kong's) LSCI would have an impact on their Asian neighbors.

To see the true substantive effect of these estimates, consider that the coefficients for the estimated impact relate to the logged LSCI. A 1% change in China's LSCI would increase its own expected value of logged merchandise trade by less than 0.78%. In Table 6, looking at the country with the greatest spillover impact from a 1% change in China's LSCI, the percentage increase in the expected value of merchandise trade would be 17.04% for Hong Kong. A 1% change in the current LSCI of Hong Kong would raise its own expected value of logged merchandise trade by less than 0.767%.

For the country with the largest spillover effect from a 1% change in Hong Kong's LSCI, the expected value of merchandise trade would increase by 4.32% for China based on these estimates.

5. Conclusions

We evaluated whether merchandise trade is related to spatially or clustered and how these connections are related. Using the model with data on spatially lagged merchandise trade was markedly more accurate than the conventional linear regression model. The spatially lagged model had a higher log-likelihood than the OLS model, which assumed that observations are independent. This supported our premise that the spatial lag of merchandise trade contributes to specifying the spread of merchandise trade far more accurately than just using an economy's LSCI. This model assumes that the merchandise trade of country i influence those of country j, which, in turn, influence those of country k. Going full circle influences the merchandise trade of country i. Different merchandise trade values for country i circulate through all of the economies in the network. Although the LSCI was not fully able to account for variances in merchandise trade in our empirical results, the association of one country's merchandise trade and those of its neighbors were extremely close.

The primary limitation of this study was the fact that the uni-directional recursive model was unable to take into account that the causality between trade and connectivity goes in both directions. Accordingly, future studies could engage in applying a Granger causality test to panel data to further investigate the relationships between trade and connectivity to

	ΔChina's LSCI		ΔHong Kong's LSCI	
Country	Spillover (%)		Country	Spillover (%)
Hong Kong	17.04		China	4.32
Korea	16.31		Korea	0.69
Taiwan	11.17		Taiwan	0.49
Myanmar	7.90		Myanmar	0.35
Pakistan	7.73		Pakistan	0.34
Japan	6.71		Japan	0.30
Vietnam	5.26		Vietnam	0.23
Philippines	5.22		Philippines	0.23
India	4.39		India	0.20
Russia	2.40		Russia	0.11

Table 6.
The percentage increase in neighboring economies' merchandise trade for 1% change in LSCI for China and Hong Kong – 10 highest values

global markets. Although the model with the spatially lagged merchandise trade fit the 157 coastal economies and territories data well, it was not determined if its performance would be acceptable for more comprehensive data problems. Further research should integrate land-locked economies and deal with spatial data of zero observations. Future studies could also explore whether considerable heterogeneity exists based on different regions' trade agreements and whether continent-specific covariates included in their regression model are unable to account for this spatial variation adequately. Moreover, annual merchandise trade data jointly produced by UNCTAD and World Trade Organization have not been disaggregated to containers or non-containerized commodities. Therefore, future studies could only take merchandise trade in manufactured goods into consideration.

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Further reading

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Appendix

Country	LSCI	Merchandise	Country	LSCI	Merchandise
Kiribati	4.42	$96	Mozambique	11.94	$8,166
Northern Mariana Islands	4.32	$139	Cyprus	22.85	$8,524
Sao Tome and Principe	6.25	$154	Republic of the Congo	4.62	$8,525
Palau	3.57	$164	Papua New Guinea	9.03	$8,830
Marshall Islands	4.2	$192	Malta	51.87	$9,205
Comoros	5.53	$221	Georgia	12.89	$9,350
Dominica	5.91	$273	Cameroon	14.9	$9,736
Tonga	4.78	$281	Iceland	11.83	$10,153
Micronesia	1.92	$295	Congo, DRC	26.45	$10,200
Saint Kitts and Nevis	3.53	$353	Sudan	19.54	$11,024
Grenada	4.57	$384	Namibia	22.8	$11,537
Saint Vincent	4.8	$388	Nicaragua	8.85	$11,782
Samoa	4.59	$407	Cuba	9.25	$13,001
Maldives	9.42	$2,338	Poland	55.8	$384,973
Fiji	11.22	$2,420	Thailand	47.29	$405,900
Montenegro	7.46	$2,617	Russian Federation	41.07	$465,158
Guyana	6.2	$2,899	UAE	73.12	$490,900
The Bahamas	27.7	$2,944	Taiwan	77.61	$497,192
Mauritania	8.41	$3,124	Spain	81.44	$584,316
New Caledonia	10.04	$3,545	Singapore	119.53	$612,696
Benin	15.6	$3,605	India	58.17	$617,032
Togo	28.71	$3,672	Mexico	42.73	$760,947
Guinea	8.39	$4,107	Belgium	86.09	$770,746
Haiti	8.61	$4,504	Canada	42.14	$791,865
Madagascar	16.44	$5,161	Italy	62.82	$866,107
Jamaica	26.57	$5,969	South Korea	112.55	$901,600
Syria	13.34	$6,300	France	67	$1,049,440
Albania	4.29	$6,631	The UK	93.63	$1,051,430
Gabon	8.68	$6,669	Hong Kong	100.5	$1,063,710
Mauritius	31.99	$6,849	The Netherlands	84.39	$1,073,550
Equatorial Guinea	3.47	$7,600	Japan	73.9	$1,251,860
Yemen	20.7	$7,770	Germany	89.76	$2,401,420
Brunei Darussalam	8.86	$8,050	China	170.85	$3,695,320
Senegal	16.27	$8,118	The USA	93.63	$3,702,830

Note: An abridged list is shown

Table A1.
Merchandise trade
data (in million
dollars) for 2016

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