A GRAVITY MODEL-NEURAL NETWORK TECHNIQUE FOR PREDICTING ECONOMICS DEVELOPMENT: A PERSPECTIVE FROM CHINA'S BELT AND ROAD INITIATIVE TRADE WITH AFRICAN COUNTRIES

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ABSTRACT

New Silk Road Initiative (SRI) is China's current global development strategy entailing land and maritime routes to improve trade relationships in Africa, Asia, and Europe regions through infrastructure investments. Quantitative evaluations of SRI to determine whether it can explicitly provide more insight into Chinese bilateral trade among its partners are needed. This necessitates the improvement of the accuracy of prediction and exploits more superior algorithms, since decision- and policy-makers have always been interested in predicting the future. Machine Learning algorithms, such as supervised artificial neural networks (ANN), are known to outperform several econometric procedures in predictions, therefore, are potentially powerful techniques to evaluate SRI.

This paper uses detailed China bilateral export data from 1990 to 2017 to analyze and evaluate the impact of SRI on Bilateral trade using ANN analysis techniques and gravity model estimations.

The results indicate that the trend of export network upgrading avails serious consideration from economic and policy perspectives. Our simulations suggest that Chinas bilateral exports flow among the new silk road countries may result in a slight increase in inter-regional trade.

This study provides a comparison view of the different estimation procedures of the gravity model – OLS, and PPML– with the artificial neural network (ANN). The ANNs associated with fixed country effects reveals a more accurate estimation when compared to a baseline model and with country-year fixed effects. Contrarily, the OLS estimator, and the poisson pseudo-maximum likelihood (PPML) showed mixed results. The ANN estimation of the gravity equation found to be superior over others when elucidating the variability of the dependent variable (export) allied with the accuracy of predictions using root mean squared error (RMSE) and R square. This research also offers policy implications for both China and its Partner Countries.

Keywords: Bilateral Trade; China Belt and Road Initiative; Gravity Model; Artificial Neural Network analysis (ANN), African Countries.

1. INTRODUCTION

China's New Silk Road, also known as Belt and Road Initiative (BRI) is an ambitious economic project aimed at building a network of overland trading routes linking China to Europe, Asia, and

Africa. This initiative underlines regional connectivity through ports and infrastructural projects. The initiative aims to strengthen infrastructure, trade, and investment links between China and some 65 other countries that account collectively for over 30% of global GDP, 62% of the population, and 75% of known energy reserves [1]. Therefore, the "Belt and Road" initiative appears to bring about a greater diversity of trade partners and trade patterns, giving the industry new opportunities to transform and upgrade itself. The BRI consists primarily of the Silk Road Economic Belt, linking China to Central and South Asia and onward to Europe; and the New Maritime Silk Road, linking China to the nations of South East Asia, the Gulf Countries, North Africa, and on to Europe. Six other economic corridors have been identified to link other countries to the Belt and the Road [1]. The scope of the initiative is still taking shape, and recently, this initiative has been interpreted to be open to all countries as well as international and regional organizations.

The Belt and Road Initiative can transform the economic environment in which economies in the region operate. Regional cooperation on the new and improved transport infrastructure and policy reforms could substantially reduce trade costs and improve connectivity, leading to higher cross-border trade and investment and improved growth in the region. In the past decade, bilateral trade flows between China and countries along the BRI showed a tendency to increase [2]. Moreover, the new silk road members have become new growth points of China's foreign trade against the background of a global economic slowdown. The Belt and Road Initiative, with unimpeded trade as one primary goal, has become a paramount new-round opening up plan and regarded as a tool for boosting China's foreign trade, especially with countries along the BRI [3]. Given the stated intention to promote trade flows among economies involved in the BRI, bilateral trade flow is a critical economic indicator used by economists and policymakers. It denotes the value of goods and services that have been exported from one country to another, inducing international trade policy as well as domestic economic policy in both countries.

Supporters convey that the New Silk Road, also called 'One Belt One Road' (OBOR) initiative, enables novel infrastructure and economic assistance to be offered to needy economies. Critics stress that it eases Chinese economic and strategic dominion of the countries along these routes. However, as a general rule, trade facilitation may reduce transaction costs, simplify trade procedures, and improve customs efficiency [4]. A plethora of studies have attempted to construct assessment systems for trade facilitation; however, they vary significantly in terms of indicators used. For instance, John Raven [5] believed that the indicators should encompass the customs environment, efficiency of payment system and business credibility. Wilson et al. [6] selected four indicators, such as port efficiency, customs environment, institutional environment, and e-commerce, to find their evaluation system. Li et al. [7] selected six indicators, including port efficiency, customs environment, institutional environment, business environment, e-commerce, and market access into the evaluation system, and made use of the entropy method to compute the trade facilitation scores of 109 countries in the world. Zhu et al. [8] used indicators based on five areas, including infrastructures and services, port efficiency, customs environment, information and communication technologies, and business environment, then adopted Delphi method and Analytic Hierarchy Process (AHP) to determine the weight of each indicator.

In connection with these, the integration of a multi-analytic technique revealed how merging two diverse data analysis approach in either methodology or analysis can improve the validity and confidence in the output [9–11]. Regarding the method used, a series of gravity models or Computable General Equilibrium (CGE) models have been extensively adopted to assess the effect of trade facilitation on trade flows [12–14]. For instance, Zhang et al. [15] took the extended trade

gravity model to research on the trade facilitation along "the Silk Road Economic Belt." Their finding revealed that it had a U-shaped distribution since Europe has shown the highest levels of trade facilitation, East Asia presented the middle levels, whereas countries in the middle of the belt presented the lowest levels, and the impact of trade facilitation on diverse regions disclosed notable heterogeneity [15]. Traditionally, the multiplicative gravity model has been linearized and evaluated using ordinary least squares (OLS) per the assumption that, the variance of the error is constant across observations (homoskedasticity), or applying panel techniques to assume that the error is constant across countries or country-pairs. However, as stressed by Santos et al. [16], when the issues of heteroskedasticity arise, OLS estimation may not be consistent and nonlinear estimators should be adopted.

From this end, integration of gravity model and artificial neural network (ANN) was applied in the field of human mobility, particularly to predict human mobility within cities based on traditional and Twitter data [17] purposively to compare their performance and results. However, there is a scarcity of this methodology regarding the study of bilateral trade flow amongst various countries. During the last decades, with the fast advancements in computer and information communication technologies (ICT), adopting artificial intelligence-based techniques in time series or panel data forecasting has become a common practice among researchers. Analytical methods that embody complex computational algorithms may offer the most practical approach for assessing a multivariate response of a New Silk Road Initiative (SRI) project amongst various countries. Precisely, neural network models use the computer-based learning method that mimics the neuronal structure of the human brain [18, 19]. Therefore, artificial neural network-based models could be used in predicting international trade estimation as a promising forecasting tool.

Following these debates in the literature, this paper aims to analyze the existing bilateral export linkages among economies regarding gross trade predominantly the bilateral trade flow between China and African Countries, which exercise reflects the international shared production linkages. Since the BRI is presented as an open arrangement in which all countries are welcome to participate, there is not an official list of "BRI countries." Different versions of unofficial lists of countries along the Belt and the Road exist, none of which received confirmation from the Government of China [3].

The study proposes to evaluate and predictive this bilateral trade grounded on the hybrid methodology such as gravity model and ANNs. The forecasting performance of the non-linear and nonparametric model (i.e., ANN) is particularly evaluated against the international model estimated by OLS regression and Poisson Pseudo Maximum Likelihood (PPML) precisely. The input to our algorithms is a set of economic and geographic variables and regional trade agreements, such as GDP, distance, and infrastructure between the importer and exporter country. Our input space will be discussed extensively in the feature section. We use linear regression, with raw features as well as logarithmic features, a kernelized linear regression, and a neural network with a variety of architectures. The output of these algorithms is a bilateral export value measured in billion US dollars ($). This study is to provide new insights into African policymakers in charge of relations with China. As stressed by Jonathan Holslag [20], an assessment of the New Silk Road, the objectives and tools to improve it, is undoubtedly significant for the academic debates about the international political economy.

The remainder of the paper is organized as follows: The next section provides the literature on bilateral trade associated with the combined method viewed as related work. Section 3 gives an overview of gravity and neural network models; Section 4 introduces the data sources and methodology; Section 5 presents the analysis and discussion, including neural network predictions

with actual trade among China and its selected BRI members. In the final section, conclusion remark entailing implications, and future research are discussed.

2. RELATED WORK

The gravity model of trade has appeared as an essential and widespread model in elucidating and predicting bilateral trade flows. Whereas the theoretical validation is no longer in doubt, its empirical application has still engendered several unresolved controversies in the literature [21, 22]. The most challenging issues related to the estimation of gravity models are the heteroscedasticity and zero trade values [22]. The disappointing performance of linear models was somehow ascribed to unrealistic assumptions associated with these models about the nature of data that do not comply with real-world situations [23].

While there are many existing works of literature on gravity models, applying machine learning methods such as artificial neural networks (ANNs) to predict trade flow remains new areas of research topic [24]. Studies have compared the forecasting performance of ANNs with univariate time series models, with macroeconomic fundamentals-based models estimated by ordinary least squares (OLS), as well as with multivariate time series models. Wu [25], Zhang [26], and Khashei et al. [27] compared the forecasting performance of autoregressive integrated moving average (ARIMA) models and ANNs in terms of RMSE and MAE. The ANNs performed substantially better than the ARIMA models. Lisi and Schiavo [28], and Leung et al. [29] employed ANNs for forecasting various exchange rates concerning the Random Walk (RW) model by adopting Normalized Mean Square Error (NMSE) and RMSE as performance criteria.

Recently, Wohl and Kennedy [30] in their study exhibited an extremely starter endeavor to examine international trade with neural network and traditional trade gravity model approach. The findings showed that the neural network has a high degree of accuracy in prediction compared to RMSE within the gravity model. Further, Athey [31], in his research paper, presented an appraisal of the early commitments of machine learning to economics, and likewise, expectations about its future contribution. He also investigated a few features from the developing econometric consolidating machine learning and causal inference, including its impacts on the nature of collaboration on research tools, and research questions. A research work performed by Nummelin and Hänninen [32] utilized the Support Vector Machine (SVM) to break down and conjecture reciprocal exchange streams of soft sawn wood.

More applicable to our target, Nuroglu [33] demonstrated that neural networks achieve a lower MSE when contrasted with panel data models by using data from 15 EU countries. Tkacz and Hu [34] also showed that financial and monetary variables could be improved using neural network techniques. Combining neural network and market microstructure approaches to investigate exchange rate fluctuations, Gradojevic and Yang [35] found that macroeconomic and microeconomic variables are valuable to forecast high-frequency exchange rate variations. Similarly, Varian [36], and Circlaeys et al. [37] provided an overview of machine learning tools and techniques, including its effect on econometrics. Furthermore, Bajari et al. [38] presented an overview and applied a few methods from statistics and computer science to the issue of interest estimation. The findings showed that machine learning combines with econometrics anticipate the request out of the test in standard measurements considerably more precisely than a panel data model.

Departing from these works, we study the estimation and the forecasting of china's export with a member of the New Silk Road Initiative using a large dataset from UN-Comtrade that includes 163 countries based on the two-stage approaches gravity model-ANN analysis.

3. MODELING

3.1. Gravity Models

Originated from Salette and Tinbergen [39] and Pöyhönen [40], the gravity model is one of the most successful empirical approaches in trade. Longtime remained opined with the traditional economic theories of trade; the gravity model is now deeply integrated with the theoretical foundations in economics with literature rich in contributions and perspective [41]. Empirical studies of bilateral trade often rely on the traditional gravity model, which relates the volume of trade between cities, countries, or regions to their economic scales and the distance between them. The basic model for trade between two countries $(i\ and\ j)$ can take the following form:

$$T_{ij} = \propto \frac{GDP_i^{\theta_1} \times GDP_j^{\theta_2}}{D_{ij}^{\theta_3}} \quad (1)$$

Where T_{ij} represents the trade volume between areas i and j; GDP_i and GDP_j are the gross domestic product of the countries $(i\ and\ j)$ that are being measured; D_{ij} is the distance between areas i and has strong j; For $\propto, \theta_1, \theta_2$ and θ_3 , they are the parameters to be estimated.

This model is intuitive, adaptable, has a substantial hypothetical establishment, and can make reasonably accurate predictions of international trade [30]. Gravity models have encountered various feedbacks. For instance, most gravity display estimations have discovered a determinedly substantial negative impact of distance on bilateral trade since the 1950s, despite exact proof on falling transport cost and globalization. Notwithstanding, Yotov [42] showed that gravity models do demonstrate a declining impact of distance on trade after some time when they represent internal trade costs. A straightforward gravity model can be enlarged in different ways. Gravity models regularly contain dummy variables factors that demonstrate whether the trade partners share a border, a language, a colonial relationship, or a regional trade agreement. As indicated by Anderson and Wincoop [41], the gravity models should represent multilateral resistance, since relative trade costs not only outright costs matter. The gravity models can catch multilateral resistance and also another country's particular historical, cultural, and geographic component, by utilizing country fixed effects: dummy factors for individually country exporter and individually country importer. Although, one weakness of this approach is that country fixed effects will ingest whenever invariant country-specific factor of intrigue [43], some gravity models employ country-year fixed effects, country-pair fixed effects, or both. Gravity models can appear as Ordinary Least Squares (OLS) estimators, for example,

$$\begin{aligned} lnX_{ij,t} = \theta_0 + \theta_1 lnGDP_{i,t} + \theta_2 lnGDP_{j,t} + \theta_3 lnDist_{ij} + \theta_4 Contig_{ij} + \theta_5 Comlang_{ij} \\ + \theta_6 Col_{ij} + \theta_7 lnInfrai_i + \theta_8 lnInfra_j + \theta_9 Obor_{ij} + \theta_{10} Asean_{ij} \\ + \theta_{11} Eac_{ij} + \theta_{12} Sadc_{ij} + \in_{ij,t} \end{aligned} \quad (2)$$

where $X_{ij,t}$represents the bilateral export between country i and country j , $GDP_{i,t}$ and $GDP_{j,t}$, the gross domestic product of partners' i and j , the distance between i and j, $Dist_{ij}$, and dummy variables entail a common border $(Contig_{ij})$, a common language ($Comlang_{ij}$), a common colony (Col_{ij}), an infrastructure index of the partner countries ($Infrai_i$ and $Infrai_j$), and

regional trade agreements ($Obor_{ij}$, $Asean_{ij}$, Eac_{ij}, $Sadc_{ij}$). For $\in_{ij,t}$, it is an error term for a pair of ith country and j^{th} in the year t. Based on the analogy of equation 2, both the country-fixed effects and country-year fixed effects can be computed and used directly through the data analysis.

Estimating the zero trade flows between the country pairs have been a big challenge. Adopting the OLS estimator in logarithmic form, the zero trade flows will be merely dumped from the estimation sample. Nevertheless, they can retain significant information. To overcome this concern, we also apply the multiplicative form of the gravity equation by non-linear Poisson Pseudo-Maximum Likelihood (PPML) estimator, which is supported as the best solution in the work of Santos Silva and Tenreyro [16, 44]. Piermartini and Yotov [45] highlighted the additional advantage of PPML estimators, such as it offers unbiased and consistent estimates even with significant heteroscedasticity in the data and a large proportion of zero trade values. Since the trade data are full of heteroscedasticity, using the log-linear OLS estimator provides not only biased outcomes but also inconsistent estimates, whereas the PPML estimator accounts for heteroscedasticity.

Contrarily to the various challenges in producing the hypothetically adjust models for causal inference, this research attempts to attain a significant predictive capacity of bilateral trade flow. From this end, our approach remains a blend of econometrics and grounded generally in gauging and deduction with particular focus on time series econometrics. The study ponders on the time series models such as AR, MA, ARMA types models. This is paramount of importance to provide hypothetical support for the usefulness of our models in assessing the fundamental mechanisms of bilateral export flow. However, we consent this is an important research objective because the measure of exports influences governments' domestic and trade arrangements, as well as a model that offers more trade volume prediction would be beneficial for policy and decision-makers.

3.2. Artificial Neural Network (ANN) Analysis

The applications of intelligent methods have emerged exponentially in recent days to research most of the non-linear parameters. Artificial neural networks (also ANNs or neural nets) are similar to non-parametric and non-linear statistical regression models [11, 46]. ANNs represent a general class of non-linear models that have been successfully applied to a variety of problems such as pattern recognition, natural language processing, medical diagnostics, functional synthesis, and forecasting (e.g., econometrics), as well as exchange rate forecasting [35]. Neural networks are especially appropriate to learn patterns and remember complex relationships in large datasets. Fully Connected Layers are very basic but yet very powerful neural network types. Their structure is mainly an array of weighted values that is recalculated and balanced iteratively. They can implement activation layers or functions to modify the output within a specific range or list of values.

ANNs are composed of simple computational elements, including an input layer, hidden layers, and an output layer. The input layer receives the input data, i.e., the set of independent variables, while the output layer computes the final values. As for the hidden layers, they let the neural network combines inputs in complex nonlinear ways, allowing computations that would not be possible with a single layer. In this work, we use a Fully Connected Network made of 20×15×10×5 nodes with four hidden layers as illustrated in Figure 1. The input features of the network are standard gravity model variables such as GDP, distance, border, colonial relationship, and trade agreement, to mention few, as summarized in Table 1.

Table 1 Features

Column name	Representation	Feature description
$lnX_{ij,t}$	Exports from China to the World (millions of US. dollars)	The logarithm of China's bilateral exports to partner country at year t
$lnGDP$ exporter	GDP, Annual %	The logarithm of GDP of China at year t
$lnGDP$ importer	GDP, Annual %	The logarithm of GDP of partner country j at year t
ln Distance	Bilateral distance (million km	The logarithm of the distance between china and partner country
$Contig$	Contiguity	1 if the two trading partners share a border a common border,0 otherwise
$Comlang_$off	Common Language	1 if the two trading partners share a common official or primary language, 0 otherwise
$Colony$	Colonial relationship	1 if one of the trading partners for origin and destination ever in a colonial relationship
$Infrai$	Infrastructure index	The logarithm of the infrastructure of China
$Infra_j$	Infrastructure Index	The logarithm of the infrastructure of partner country j at year t
$Obor$	Belt and Road initiative, Dummy	1 if the origin country is an OBOR member
$Asean$	Association of Southeast Asian Nations, Dummy	1 if the origin country is an ASEAN member
Eac	East African Community, Dummy	1 if the origin country is an EAC member
$Sadc$	Southern African Development Community, Dummy	1 if the origin country is a SADC member

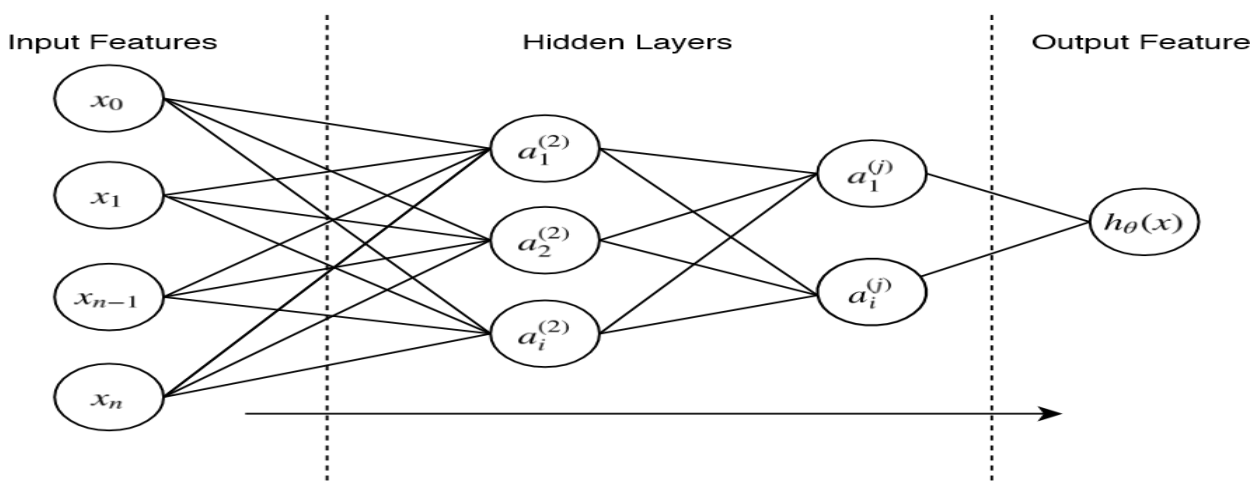

Fig. 1. Fully Connected Neural Network Model

The output neuron can be computed as follow:

$$\alpha = f\left(\sum_{i=0}^{N} w_i\, x_i\right) \tag{3}$$

where f is the activation function, x_i denoted the numerical input and the weights are represented by w_i. There have been various activation functions that are applied in the context of ANNs. One commonly used activation function is the sigmoid function, which takes a value between 0 and 1 by applying a threshold. However, we will be using the rectified linear unit (ReLU) as the activation function. ReLU function refers to the type of activation function returning to the max (0, x). The two activations function are depicted in Figure 2 below.

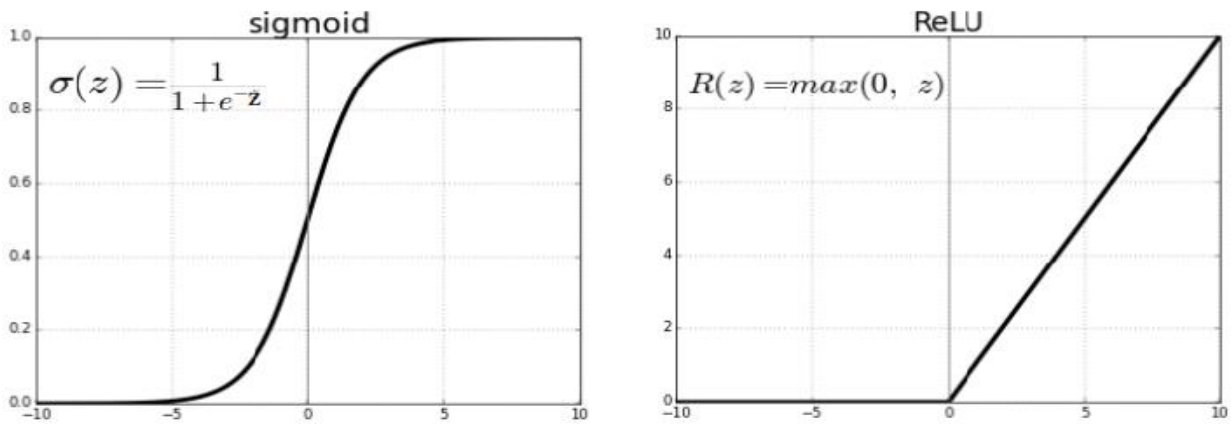

Fig. 2. Activation Functions: Sigmoid Function and Rectified Linear Unit (ReLU)

4. DATA SOURCES AND METHODOLOGY

4.1. Dataset

The study uses the data which covers a panel data set of 162 countries from 1990 to 2017. Therefore, our data set entailing 4536 observations of bilateral export flows (162 × 161 country pairs). There are various sources of data that were applied for data analysis.

UN-Comtrade database was used to obtain the data for bilateral trade (exports), while the World Development Indicators (WDI, 2018) was utilized as a source for GDP (importer, exporter) in billions current U.S. dollars. Data on location and dummies indicating contiguity (common border), common language (official language), colony (colonial relationship), were taken from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The Bilateral distance between China and its partners was taken from the CEPII distance database. The Infrastructure index grounded in Carrere and Grigoriou [47], and Limao [48] approach is computed by applying four variables proxying the transport infrastructure from the IRF world road statistics and WDI (WB,2018): total roads network, total paved Roads, railway network, and number of telephones mainline per person. The model was estimated using China's bilateral exports between its new silk road partners. The summary of the 13 economic features that are used in our model is presented in Table1 (Features). GDP and the amount of exports are reported in current US $. Most of these features are commonly applied in the structure of the Gravity Model and therefore are all deemed well-defined, based on a strong background and suitable for this study. Implementing these

features for the prediction purpose allows us to compare our performance against the Gravity Model, which is our baseline model.

4.2. Cleaning Techniques and Features

To avoid deviations in data and potential obstacles in the procedure of prediction, we have applied several data cleaning techniques before we start our analysis. Firstly, we extrapolate the missing data using the preprocessing methods. Secondly, we removed incomplete data from the data set. That is, we did not work with data points that have missing feature values. Thirdly, we removed all trade flow values that have no values, as they are not economically significant and cause outlier problems. Fourthly, we took the log of data to achieve a smoother distribution of the data, as shown in figure 3. At last, we removed data before 1990 to 1991, as our focus is to predict recent trade flows. For the neural network, we standardize the continuous variables (exporter's GDP, importer's GDP), scaling them so that their means equal zero, and their standard deviations equal one using Equation 4.

$$X_S = \frac{x_i - mean(x)}{stdev(x)} \tag{4}$$

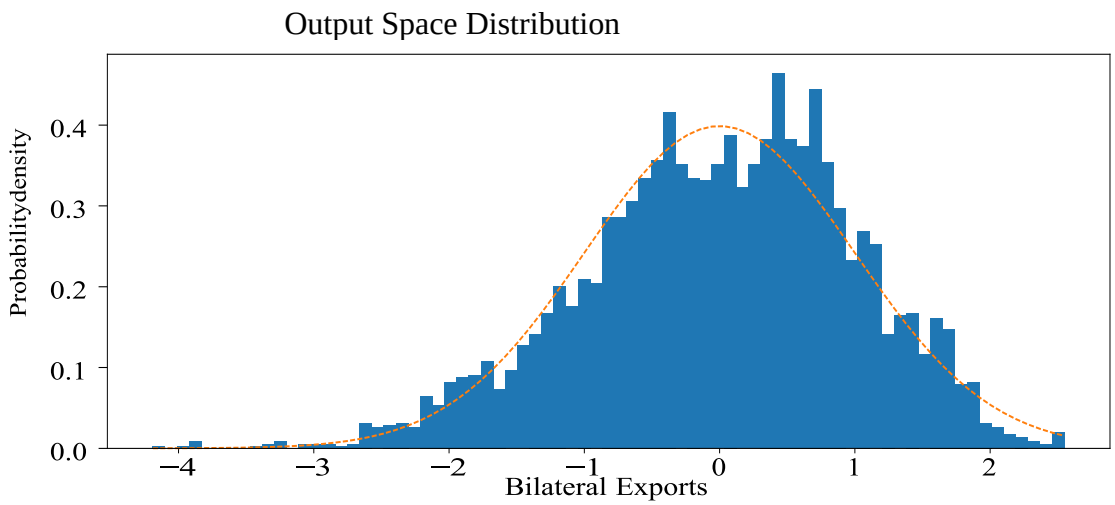

Fig.3. Histogram of feature space distribution of bilateral exports

5. ANALYSIS AND DISCUSSION

The gravity model is regarded as the workhorse tool in examining international trade. It measures the relationship between the trading behavior of two countries based on their GDPs and distances. It offers accurate predictions of international trade and has strong theoretical foundations [30]. The outputs of gravity model estimations are compared to the outputs of neural networks using the MSE (mean squared error) and RMSE (root mean squared error) as well as other metrics that may be used alongside. MSE is a squared RMSE, an absolute measure of fit, and is reported in the same unit as the response variable.

Table 2 shows the results of the evaluations. For the baseline dataset, the OLS estimator has an out-of-sample root mean squared error of $16.05 billion, the PPML estimator has an out-of-

sample RMSE of $6.53 billion, and the neural network has an out-of-sample RMSE of $3.83 billion. For the dataset with country fixed effects, the OLS estimator has an out-of-sample RMSE of $11.30 billion, the PPML estimator has an out-of-sample RMSE of $9.79 billion, and the neural network has an out-of-sample RMSE of $1.91 billion. For the dataset with country-year fixed effects, the OLS estimator has an out-of-sample RMSE of $6.66 billion, the PPML has an out-of-sample RMSE of $8.17 billion, and the neural network has an out-of-sample RMSE of $1.89 billion. These analyses were repeated several times, allowing for variation both in the random training-test division and the development of the neural network, and these outcomes are representative. To illustrate the forecasting application of our model, we trained the neural network on the full dataset with country fixed from 1990 to 2012 and use it to predict bilateral trade export between China and its major trading partners in the Silk and Road Initiative. The estimation covers the period from 2013 to 2017.

The accuracy of the network models is measured by RMSE [11, 49], which is calculated as the difference between actual and predicted values of the dependent constructs, i.e., export in the present context. We provided the result of the neural network with the actual GDPs of China and its BRI partners as seen from Table 3 and Figure 4. The neural network's estimations are reasonably close to actual trade values even 5 years beyond the training period.

Table 2 Trade Predictions using Estimators in respect to Generated RMSE (In Millions of US $)

Models	OLS	PPML	Neural Networks
Baseline Model	$16.05	$6.53	$3.83
Country-fixed effects	$11.30	$9.79	$0.1908
Country-year fixed effects	$6.66	$8.17	$1.89
Adjustment and architecture	Dependent variable: $ln(X_{ij}+1)$	Dependent variable $X_{ij,t}$	Exports, distance, infrastructure, GDP, $(standardized\ mean = 0)$ $(Std.Dev. = 1)$

Table 3 Neural Network Predictions Versus Actual Trade Values (in Millions Us $)

Countries	Predictions	2013	2014	2015	2016	2017
Kenya	Actual	6.5075	6.6929	6.7719	6.7472	6.7472
	Predicted	6.5595	6.6094	6.6306	6.6550	6.6911
Rwanda	Actual	5.1275	5.0606	5.0873	5.0356	5.0356
	Predicted	5.02705	5.0700	5.0933	5.0966	5.1489
Zimbabwe	Actual	5.6168	5.6062	5.7351	5.5883	5.5882
	Predicted	5.8410	5.8689	5.8860	5.8881	5.9284

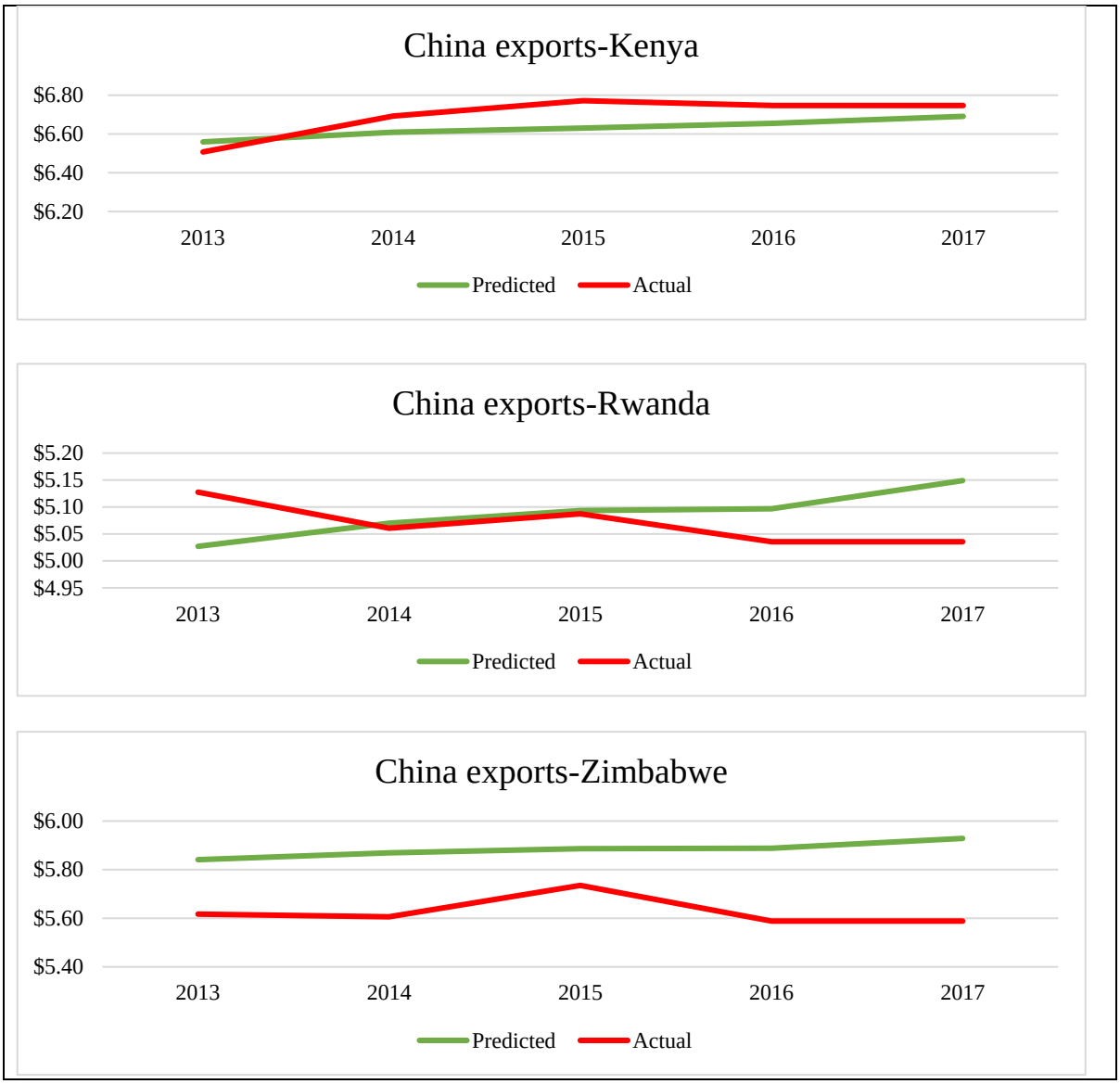

Figure 4. Neural network predictions compared to actual trade

Table 4 below presents a summary of the models' performances. The table reports both the average RMSE values as well as the values of R^2 . These values were used to predict the correctness of the Gravity and ANN models. The smaller the value of RMSE, the better the accurateness of the prediction. R^2 ranges from 0 to 1: If $R^2 = 0$, the model always fails to predict the target variable, and if $R^2 = 1$ the model perfectly predicts the target variable. Any value between 0 and 1 signposts what percentage of the target variable, applying the model, can be elucidated by the features. If $R^2 < 0$ it reveals that the model is no better than one that continually predicts the mean of the target variable.

The output of the traditional gravity model (OLS) was used to compare the output of neural networks to some extent. However, particular attention was put on the PPML (considered as the more robust estimator to deal with the panel data and non-linearity data set) for the comparison with ANN outputs. As shown from Table 4, the result of the gravity model is assessed against the ANN model in term of RMSE and R^2. The neural network with country fixed effects has the

greatest predictive accuracy among the models. It attains a 98.05 percent reduction in out-of-sample RMSE in comparison with the PPML estimator on the same dataset and a 98.32 percent reduction as compared to the OLS estimator.

Moreover, using the identical set of features as the Gravity model (baseline model) based on the OLS estimator, the ANN technique (baseline model) achieves a notable improvement of above 0.49 in the test set's R^2 score. Similarly, using the identical set of features as the Gravity model (baseline model) grounded in PPML estimator, the ANN technique (baseline model) achieves a remarkable improvement of above 0.03 in the test set's R^2 score. This appears to signpost that neural networks are successful at discovering non-linear interactions between features compared to the Gravity model, mainly with OLS estimator which is a purely linear model of logarithmic features. This result discloses that we were able to achieve higher predictive ability without calling into time series models, which was one of the purposes of the research work.

Table 4 Average RMSE and R^2 comparison between Gravity models and ANN

Models	Indices	Gravity model		Neural Network	Compared Gravity Model and ANN	
		OLS	PPML	ANN	OLS-ANN	PPML-ANN
Baseline Model	RMSE	$16.05	$6.53	$3.83	$12.22	$2.70
	R^2	$0.46	$0.91	$0.95	($0.49)	($0.03)
Country-fixed effects	RMSE	$11.30	$9.79	$0.19	$11.11	$9.60
	R^2	$0.74	$0.91	$0.94	($0.19)	($0.03)
Country-year fixed effects	RMSE	$6.66	$8.17	$1.89	$4.77	$6.28
	R^2	$0.91	$0.93	$0.97	($0.06)	($0.05)

NB: Values in bracket are the negative R^2 values obtained either as a difference between OLS and ANN or PPML and ANN.

6. CONCLUDING REMARKS

It remains useful to understand why trade happens the way it arises and to expand economic ties between countries, a theoretical question that can be facilitated through gravity models employing traditional specifications. Moreover, predicting the trade between two countries (i.e., China and African' Countries) with a high degree of accuracy is an essential and practical inquiry that can be patronized by neural networks. This study corroborates that China's bilateral exports flow under the new silk road initiatives could have a significant positive effect on the countries involved. Our simulations have shown that using neural networks is a promising approach in predicting bilateral trade flow when we are making predictions with other economic variables of the same time period. Neural network techniques are a sound methodology for making predictions about economic data.

This paper compares the various estimation procedures of the gravity model – OLS, and PPML– with the neural network. Employing the same set of features as the Gravity model (baseline model) based on the OLS estimator, the ANN technique (baseline model) achieves a notable improvement of above 0.49 in the test set's R^2score. In the similar vein, the same set of features as Gravity model (baseline model) grounded in the PPML estimator, the ANN technique (baseline model) attains a remarkable improvement of above 0.03 in the test set's R^2score. The neural networks associated with fixed country effects showed a more accurate estimation as compared to

a baseline model even with country-year fixed effects. For the OLS estimator and Poisson pseudo-maximum likelihood (PPML); however, they showed mixed results.

It appears that the neural network estimation of the gravity equation is found superior over the other procedures in terms of explaining the variability of the dependent variable (export) regarding the accuracy of predictions using RMSE and R square. The scope of the gap in predictive accuracy recommends that neural networks are capturing non-linear interactions of independent constructs that influence trade in ways not captured by OLS or PPML models. The results stress, then, that we were able to achieve higher predictive ability without calling into time series models, which was one of the drives of the research work.

Policymakers, analysts, and businesses would all be able to profit by exact scales about China's bilateral exports among its new silk road members. One heading for future research is to utilize neural networks to anticipate the impacts of intra-regional trade or regional integration. Future research subjects could apply alternative artificial neural network structures such as radial basis function neural networks and recurrent neural networks instead of multilayer multi-Layer perceptron neural networks and using the output of the PPML model as inputs to artificial neural networks.

REFERENCES

[1] Huang, Y. Understanding China's Belt & Road Initiative: Motivation, Framework and Assessment. *China Econ. Rev.*, **2016**. https://doi.org/10.1016/j.chieco.2016.07.007.

[2] Du, J.; Zhang, Y. Does One Belt One Road Initiative Promote Chinese Overseas Direct Investment? *China Econ. Rev.*, **2018**. https://doi.org/10.1016/j.chieco.2017.05.010.

[3] Boffa, M. Trade Linkages Between the Belt and Road Economies (English). *Policy Res. Work. Pap.*, **2018**. https://doi.org/10.1596/1813-9450-8423.

[4] Moïsé, E.; Sorescu, S. Trade Facilitation Indicators. *OECD Trade Policy Papers no.144*. 2013. https://doi.org/10.1787/5k4bw6kg6ws2-en.

[5] Raven, J. *Trade and Transport Facilitation: A Toolkit for Audit, Analysis, and Remedial Action*; Washington, DC, USA, 2001.

[6] Wilson, J. S.; Mann, C. L.; Otsuki, T. Trade Facilitation and Economic Development: A New Approach to Quantifying the Impact. *World Bank Econ. Rev.*, **2003**, *17* (3), 367–389. https://doi.org/10.1093/wber/lhg027.

[7] Li, B.; Duan, Y. Trade Facilitation Assessment and Its Impact on China's Service Trade Exports: Based on Transnational Panel Data Empirical Research (in Chinese). *Int. Bus*, **2014**, *1*, 5–13.

[8] Zhu, J. B.; Lu, J. Research and Application of Trade Facilitation Evaluation Indicator System (in Chinese). *J. Hunan Univ.*, **2015**, *6*, 70–75.

[9] Scott, J. E.; Walczak, S. Cognitive Engagement with a Multimedia ERP Training Tool: Assessing Computer Self-Efficacy and Technology Acceptance. *Inf. Manag.*, **2009**, *46* (4),

221–232. https://doi.org/10.1016/j.im.2008.10.003.

[10] Gbongli, K. A Two-Staged SEM-AHP Technique for Understanding and Prioritizing Mobile Financial Services Perspectives Adoption. *Eur. J. Bus. Manag.*, **2017**, *9* (30), 107–120.

[11] Gbongli, K.; Xu, Y.; Amedjonekou, K. M. Extended Technology Acceptance Model to Predict Mobile-Based Money Acceptance and Sustainability: A Multi-Analytical Structural Equation Modeling and Neural Network Approach. *Sustainability*, **2019**, *11* (13), 1–33. https://doi.org/10.3390/su11133639.

[12] Dennis, A. *The Impact of Regional Trade Agreements and Trade Faciliation in the Middle East North Africa Region*; Washington, DC, USA, 2006.

[13] ZAKI, C. An Empirical Assessment of the Trade Facilitation Initiative: Econometric Evidence and Global Economic Effects. *World Trade Rev.*, **2014**, *13* (1), 103–130. https://doi.org/10.1017/S1474745613000256.

[14] Iwanow, T.; Kirkpatrick, C. Trade Facilitation and Manufactured Exports: Is Africa Different? *World Dev.*, **2009**, *37* (6), 1039–1050. https://doi.org/10.1016/j.worlddev.2008.09.014.

[15] Zhang, Y. B.; Liu, J. Trade Facilitation Measurement of the "Silk Road Economic Belt" and China's Trade Potential (in Chinese). *Financ. Sci.*, **2016**, *5*, 112–122.

[16] Silva, J. M. C. S.; Tenreyro, S. The Log of Gravity. *Rev. Econ. Stat.*, **2006**, *88* (4), 641–658. https://doi.org/10.1162/rest.88.4.641.

[17] Pourebrahim, N.; Sultana, S.; Thill, J. C.; Mohanty, S. Enhancing Trip Distribution Prediction with Twitter Data: Comparison of Neural Network and Gravity Models. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery, GeoAI 2018*; 2018. https://doi.org/10.1145/3281548.3281555.

[18] Garson, G. . Interpreting Neural Network Connection Weights. *Artif. Intell. Expert*, **1991**, *6*, 46–51.

[19] Ripley, B. D. *Pattern Recognition and Neural Networks*; Cambridge University Press: Cambridge, 1996. https://doi.org/10.1017/CBO9780511812651.

[20] Holslag, J. How China's New Silk Road Threatens European Trade. *Int. Spect.*, **2017**, *52* (1), 46–60. https://doi.org/10.1080/03932729.2017.1261517.

[21] Kareem, F. O. Modeling and Estimation of Gravity Equation in the Presence of Zero Trade : A Validation of Hypotheses Using Africa ' s Trade Data. In *The the 140th EAAE Seminar : Theories and Empirical Applications on Policy and Governance of Agri-food Value Chains*; European Association of Agricultural Economists: Perugia, Italy 163341,

2013.

[22] Mnasri, A.; Nechi, S. New Approach to Estimating Gravity Models with Heteroscedasticity and Zero Trade Values. *SSRN Electron. J.*, **2019**, *MPRA Paper*. https://doi.org/10.2139/ssrn.3367440.

[23] Khashei, M.; Bijari, M.; Raissi Ardali, G. A. Improvement of Auto-Regressive Integrated Moving Average Models Using Fuzzy Logic and Artificial Neural Networks (ANNs). *Neurocomputing*, **2009**, *72* (4–6), 956–967. https://doi.org/10.1016/j.neucom.2008.04.017.

[24] Dumor, K.; Yao, L. Estimating China's Trade with Its Partner Countries within the Belt and Road Initiative Using Neural Network Analysis. *Sustainability*, **2019**, *11* (5), 1449. https://doi.org/10.3390/su11051449.

[25] Wu, B. Model-Free Forecasting for Nonlinear Time-Series (with Application to Exchange-Rates). *Comput. Stat. Data Anal.*, **1995**, *19* (4), 433–459.

[26] Zhang, G. P. Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model. *Neurocomputing*, **2003**, *50*, 159–175. https://doi.org/10.1016/S0925-2312(01)00702-0.

[27] Khashei, M.; Rafiei, F. M.; Bijari, M. Hybrid Fuzzy Auto-Regressive Integrated Moving Average (FARIMAH) Model for Forecasting the Foreign Exchange Markets. *Int. J. Comput. Intell. Syst.*, **2013**, *6* (5), 954–968. https://doi.org/10.1080/18756891.2013.809937.

[28] Lisi, F.; Schiavo, R. A. A Comparison between Neural Networks and Chaotic Models for Exchange Rate Prediction. *Comput. Stat. Data Anal.*, **1999**, *30* (1), 87–102. https://doi.org/10.1016/S0167-9473(98)00067-X.

[29] Leung, M. T.; Chen, A.-S.; Daouk, H. Forecasting Exchange Rates Using General Regression Neural Networks. *Comput. Oper. Res.*, **2000**, *27* (11–12), 1093–1110. https://doi.org/10.1016/S0305-0548(99)00144-6.

[30] Wohl, I.; Kennedy, J. *Neural Network Analysis of International Trade*; ID-049; Washington, DC, 2018.

[31] Athey, S. The Impact of Machine Learning on Economics. In *in: The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press, 2018; pp 507–547.

[32] Nummelin, T.; Hänninen, R. *Model for International Trade of Sawnwood Using Machine Learning Models*; 74/2016; Helsinki, 2016.

[33] Nuroglu, E. Estimating and Forecasting Trade Flows by Panel Data Analysis and Neural Networks. *Istanbul J. Econ.*, **2014**.

[34] Tkacz, G.; Hu, S. *Forecasting GDP Growth Using Artificial Neural Networks*; 99-3; Ottawa, Ontario, Canada, 1999.

[35] Gradojevic, N.; Yang, J. *The Application of Artificial Neural Networks to Exchange Rate Forecasting: The Role of Market Microstructure Variables*; 2000-23; Ottawa, Ontario, Canada, 2000.

[36] Varian, H. R. Big Data: New Tricks for Econometrics. *J. Econ. Perspect.*, **2014**. https://doi.org/10.1257/jep.28.2.3.

[37] Circlaeys, S.; Kanitkar, C.; Kumazawa, D. Bilateral Trade Flow Prediction.

[38] Bajari, P.; Nekipelov, D.; Ryan, S. P.; Yang, M. Machine Learning Methods for Demand Estimation. In *American Economic Review*; 2015. https://doi.org/10.1257/aer.p20151021.

[39] Salette, G.; Tinbergen, J. Shaping the World Economy. Suggestions for an International Economic Policy. *Rev. économique*, **1965**. https://doi.org/10.2307/3498790.

[40] Pöyhönen, P. A Tentative Model for the Volume of Trade between Countries. *Weltwirtsch. Arch.*, **1963**.

[41] Anderson, J. E.; Van Wincoop, E. Gravity with Gravitas: A Solution to the Border Puzzle. *Am. Econ. Rev.*, **2003**. https://doi.org/10.1257/000282803321455214.

[42] Yotov, Y. V. A Simple Solution to the Distance Puzzle in International Trade. *Econ. Lett.*, **2012**, *117* (3), 794–798. https://doi.org/10.1016/j.econlet.2012.08.032.

[43] Baier, S. L.; Bergstrand, J. H. Bonus Vetus OLS: A Simple Method for Approximating International Trade-Cost Effects Using the Gravity Equation. *J. Int. Econ.*, **2009**. https://doi.org/10.1016/j.jinteco.2008.10.004.

[44] Santos Silva, J. M. C.; Tenreyro, S. Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator. *Econ. Lett.*, **2011**, *112* (2), 220–222. https://doi.org/10.1016/j.econlet.2011.05.008.

[45] Piermartini, R.; Yotov, Y. V. V. *Estimating Trade Policy Effects with Structural Gravity*; 2016.

[46] Azizi, N.; Rezakazemi, M.; Zarei, M. M. An Intelligent Approach to Predict Gas Compressibility Factor Using Neural Network Model. *Neural Comput. Appl.*, **2019**, *31* (1), 55–64. https://doi.org/10.1007/s00521-017-2979-7.

[47] Carrere, C.; Grigoriou, C. *Landlockedness, Infrastructure and Trade:New Estimates for Central Asian Countries*; ffhalshs-00556941, 2011.

[48] Limao, N. Infrastructure, Geographical Disadvantage, Transport Costs, and Trade. *World Bank Econ. Rev.*, **2001**. https://doi.org/10.1093/wber/15.3.451.

[49] Chong, A. Y. L. A Two-Staged SEM-Neural Network Approach for Understanding and Predicting the Determinants of m-Commerce Adoption. *Expert Syst. Appl.*, **2013**, *40* (4), 1240–1247. https://doi.org/10.1016/j.eswa.2012.08.067.