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Estimating United States-Asia Clothing Trade: Multiple Regression vs. Artificial Neural Networks*

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Abstract

This study discusses the influence of economic factors on the clothing exports from China and 15 South and Southeast Asian countries to the United States. A basic gravity trade model with three predictors, including the GDP value produced by exporting and importing countries and their geographical distance was established to explain the bilateral trade patterns. The conventional approach of multiple regression and the novel approach of Artificial Neural Networks (ANNs) were developed based on the value of clothing exports from 2012 to 2018 and applied to the trade pattern prediction of 2019. The results showed that ANNs can achieve a more accurate prediction in bilateral trade patterns than the commonly-used econometric analysis of the basic gravity trade model. Future studies can examine the predictive power of ANNs on an extended gravity model of trade that includes explanatory variables in social and environmental areas, such as policy, initiative, agreement, and infrastructure for trade facilitation, which are crucial for policymaking and managerial consideration. More research should be conducted for the examination of the balance between developing countries' economic growth and their social and environmental sustainability and for the application of more advanced machine-learning algorithms of global trade flow examination.

Keywords: Artificial Neural Networks, China, Clothing Trade, Economic, Gravity Trade Model

JEL Classification Code: B17, B23, C01, C21, C45

1. Introduction

Asia is a key manufacturing location and exporter of clothing products. Since the nineties, China has become a foremost exporter and manufacturer within the region and in the industry (Lau, Chan, & Nguye, 2017). Nevertheless, labor shortages and escalating production costs have driven many companies to move their more labor-intensive production processes from this country to other lower-cost countries, including Cambodia, the Philippines, Vietnam, Bangladesh, and Sri Lanka (Chan & Gunasekaran, 2020).

Formally publicized in 2013, China initiated the development strategy, called the Belt and Road Initiative (BRI). This initiative is also publicly known as One Belt, One Road. This project is to build a large scale of infrastructures to improve trade and economic routes among Asian countries, and other countries. Aside from compounding new and old projects, it heavily involves an all-embracing geographic scope and puts in all-out efforts in strengthening both soft and hard infrastructure, and cultural ties. This is an initiative covering a large number of projects broadly conceived to make a more effective flow of people, goods, and investment. The connections the BRI deliberately fostered are believed to redirect economic activity, rebuild relationships, and shift power within and among states.

In addition to establishing stronger connectivity of the country with the world, this would allow many businesses

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to successfully cope with some of the risks and barriers of relocation (Chan, Danny, Yip, Cheung, & Gunasekaran, 2019; Ho, Chan, Gunasekaran, & Yip, 2020). The BRI aims to foster economic cooperation of African, Asian and European countries. One of the major outcomes of this initiative is the development of infrastructures across the "Silk Road Economic Belt" and the "21st Century Maritime Silk Road" to increase the free flow of trade and allow the resources' efficient allocation across various markets.

In terms of Asia's clothing industry, BRI possibly will propound prospective expansion and trading opportunities, in which the businesses having production facilities in China are able to relocate to Asian lower-cost countries, which are part of the BRI. The establishment of clothing production processes in these developing and emerging economies not only could promote their economic development with the creation of more job opportunities but also improve their social welfare.

The United States (US) and European Union (EU) are the largest markets in the world for clothing products, and together comprised 54% of Asia's clothing exports in 2018 (HKTDC, 2018). According to Comtrade (2019), in 2015, the clothing import to the US had been completely rising, achieving a record high of USD85 billion (see Figure 1). In 2019, the US imported USD84 billion of clothing products from the world, indicating an amount of 8% growth from USD77 billion in 2012. By value, Asian countries have been the leading clothing exporters for the US market, with China as the largest clothing supplier, capturing 36% market share, followed by Vietnam (11%), India (8%), Mexico (5%) and Bangladesh (5%) (Trade Statistics, 2019).

On the other hand, trade patterns are anticipated to change due to the current Sino-US trade war. More South and Southeast Asian countries, such as India and Vietnam respectively, can potentially become the major exporters of clothing products to the US due to the imposed tariffs on Chinese goods. In the initial rounds of the trade war, the US has implemented an amount of 10% tariff mainly on industrial equipment and machinery. However, by the third round of US tariffs on Chinese goods in September 2018,

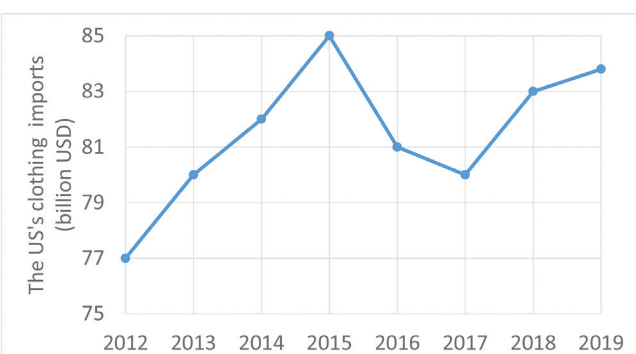

Figure 1: The United States' Clothing Imports

the tariffs had increased from 10% to 25% and the list was extended to include various consumer products, including products in the major textile categories (e.g., silk, wool products, cotton, human-made textiles) and certain fabrics (e.g., corduroy, terry towel, lace, and embroidery). The fourth round of US tariffs on Chinese goods took effect on September 1st, 2019, and clothing categories were also included on the list of tariff goods (Office of the United States Trade Representative, 2019). This has a considerable impact on many clothing businesses with production lines rooted in China or businesses sourced from China.

In light of the volatility of the trade patterns between the US and China, this study used the basic gravity model of trade to predict clothing trade patterns between the US and South or Southeast Asia countries, including China. The gravity model is commonly used to estimate the trade value between countries and how various economic factors influence the trade value (Chan, Au, & Sarkar, 2008). The model is usually examined by multiple regression analysis in empirical studies.

In more recent literature, artificial neural networks (ANNs) have been applied to predict or gauge complex trade relationships (e.g., Dumor & Yao, 2019; Wohl & Kennedy, 2018). ANNs are considered to be useful to learn patterns and remember complex relationships in large datasets (Dumor & Yao, 2019). However, there is insufficient research using ANNs to examine global trade in the textile and clothing sector. To contribute to the empirical literature of trade, this study compares the predictive power of ANNs and multiple regression in the clothing exports analysis from South or Southeast Asian countries to the US.

This paper is organized as follows: Section 2 discusses the theoretical framework of the gravity trade model and neural network analysis for trade estimation. In addition, Section 3 presents the dataset and research methodology. Section 4 summarizes the findings of the gravity trade model and neural network models, and Section 5 shows the discussion of results. Finally, Section 6 gives the conclusion with suggestions for future research recommendation.

2. Literature Review

This section introduces and describes the theoretical framework of the gravity trade model to give the detail of the conceptual basis existing in this study. Furthermore, this section brings previous studies applying the gravity model in international trade and the configuration of the baseline gravity trade model and ANN for the prediction of clothing trade.

2.1. Gravity Trade Model

In research of international trade, the gravity trade model has been universally applied to explain the spatial interactions of trade flow (Au & Chan, 2008; Bayoumi & Eichengreen, 1995; Havrylyshyn & Pritchett, 1991). Originally, Newton's equation of gravity in physics inspired this model. Expounding trade existing between the two countries derived from the economic analogue of their mutual gravitational force, by virtue of their own GDPs displaying mass, brings us the logical principles for a bilateral trade gravity model.

In international business, the gravity trade model can interpret the relationship between two trading partners. The pioneers of the development of this method, Tinbergen (1962) and Pöyhönen (1963), in their studies on bilateral trade existing between European countries, argued that the trade volume of two countries is precisely related to their national income (gross domestic product (GDP)), and is conversely related to their geographical distance. This means that high-income countries show a tendency to trade more in absolute terms, and that greater distance among countries, since it could push up the cost of transportation, would result in reduced bilateral trade (Dell'Ariccia, 1999).

2.2. Theoretical Underpinnings of Gravity Model Application in International Trade

To bring the gravity model theoretical foundation and to justify its use within international trade studies, some studies have been conducted by Anderson (1979).

In international trade, the theoretical models primarily include three models. They are the intra-industry trade model, the Heckscher–Ohlin (H–O) model, and the Richardian model. The models vary in the way to obtain product specialization in equilibrium, increasing returns to scale at the firm level in the intra-industry trade model, the differences of factor endowment (supply) in the H–O model and technology or the differences of productivity across countries in the Ricardian model (Evenett & Keller, 2002). Anderson & Van Wincoop (2003) and Bergstrand (1985, 1989) derived the gravity equations from trade models with product differentiation and increasing returns to scale. Additionally, Bergstrand (1989) and Helpman & Krugman (1985) proposed an analytical framework to understand the gravity equation which is consistent with inter-industry and intra-industry trade modern theories.

Deardorff (1998) asserted that the gravity equation is congruent with several Ricardian and Heckscher–Ohlin model variants. He added that it is fairly uncomplicated to validate the gravity equation, even its simple forms, from theories of standard trade. Nevertheless, a portion of these studies demanded homothetic preference assumption for traded goods and transportation cost (Anderson, 1979; Deardorff, 1998). Apparently, several recent studies have also highlighted these limitations in their gravity trade model applications. Frankel (1998) stated that the gravity trade model has already gone from embarrassing poverty of theoretical foundations to an embarrassment of riches.

2.3. Theoretical Properties of the Gravity Model

The basic gravity follows the equation:

$$T_{ij} = \mathrm{A}\frac{Y_i \times Y_j}{D_{ij}} \tag{1}$$

T_{ij} = Total value of trade between countries i and j
A = Constant
Y_i = GDP of country i
Y_j = GDP of country j
D_{ij} = Distance between countries i and j

In the empirical trade literature, this equation has been log-linearized and estimated by lease squares. In this study, the basic gravity model of trade is expressed as follows:

$$\log(\mathrm{Export}_{ijt}) = \alpha + \beta_1 \log(D_{ij}) + \beta_2 \log(\mathrm{GDP}_{it}) + \beta_3 \log(\mathrm{GDP}_{jt}) + \varepsilon_{ijt} \tag{2}$$

α = Intercept
Export_{ijt} = Value of Clothing (in USD) Exported from the Country i to the Country j (i.e., the US) at Time t
D_{ij} = Geographical Distance (in km) between the Capitals of Countries i and j
GDP_{it} = GDP in USD of the Country i at time t
GDP_{jt} = GDP in USD of the US at Time t
ε_{ijt} = Error Term

The gravity model of trade has been adopted in several international business studies in the textile and clothing literature (e.g., Au & Chan 2008; Chan & Au 2007; Chan et al. 2008; Chi & Kilduff, 2010; Djankov, Freund, & Pham, 2010; Lau & Bilgin 2010; Tsang & Au 2008) to explain trade among countries. These studies' findings promote the proposition that a higher GDP drives trade, whilst a greater distance impedes it.

Bergstrand (1985, 1989) adopted this model further along with Armington (1969) who assumed and asserted that the bilateral trade value deals with the function of transportation costs and income. Helpman and Krugman (1985) also argued that the gravity model could come from the monopolistic competition model with increasing returns to scale.

According to Deardorff (1998), the gravity model is in line with the Heckscher–Ohlin model in product differentiation exclusion. Apart from these, Eaton & Kortum (2002) produced the gravity-type relationship based on Ricardian's model of trade for homogenous goods. An exhaustive review of the gravity model written by Harrigan (2002) in connection with various trade models carried the monopolistic competition models, the general equilibrium model and the Armington model. Thus, in recent years, the gravity model has become an essential part of the models for trade analysis.

To identify the major determinants of clothing exports from selected Asian countries to the US market, this study holds various factors in great esteem. GDP is used to understand the influence of the monetary condition of the workforce in exporting countries on clothing trade, as well as to highlight the effect of clothing exports on the economy and the supply capability of materials of the selected country since the clothing industry is labor-oriented. To satisfy the curiosity about the situation of the importer's economy on the clothing trade, the US GDP is included in the list of independent variables (Hye, Wizarat, & Lau, 2016, Lee & Xuan, 2019). Distance is carefully weighed since it often plays a crucial role in bilateral trade (Bergstand, 1985; Bergstand, 1989; Chan & Gunasekaran, 2020; Frankel & Rose, 2002; Linnemann, 1966).

2.4. Artificial Neural Networks (ANN)

ANN is a massively parallel computing system with many interconnected simple processors, which may solve challenging computational issues such as clustering or categorization, prediction or forecasting, and pattern classification (Jain, Mao, & Mohiuddin, 1996). Considering the higher accessibility of big data and stronger and cheaper computing power, the application of ANNs is growing in different sectors. One area is the analysis of global trade patterns by ANNs, which could deliver higher predictive power.

Consistent with past studies (e.g., Dumor & Yao, 2019; Wohl & Kennedy, 2018), this study measures the prediction accuracy of multiple regression analysis of panel data and ANNs by two metrics, including the coefficient of determination (R^2) and the root mean squared error (RMSE). The predictive ability of a multiple regression model is measured by evaluating the size of R^2. In this study, the size of R^2 denotes the proportion of the variance in clothing exports that can be predicted based on three independent variables, the GDPs of the exporter, the GDPs of the importer, and distance between the exporter and importer. RMSE is the square root of the mean squared error (MSE), which is the average of the squared errors spotted between the predicted and the actual values of clothing exports, as the following equation:

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}} \tag{3}$$

$\hat{Y}_i$ = Predicted Export Value

y_i = Actual Export Value

n = Number of Predicted Export Values

3. Methodology

This section introduces a set of systemic analyses this study applied, including the dataset, multiple regression with panel data, and ANN implementation and configuration.

3.1. Dataset

With the basic gravity trade model, this study calculates the value of clothing exports to the US from 16 South and Southeast Asian countries. Six South Asian countries, which are Bangladesh, China, India, Nepal, Pakistan, and Sri Lanka, and ten Southeast Asian countries, which are Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Singapore, Thailand, the Philippines and Vietnam were examined. Timor-Leste is one of Southeast Asian countries, however, this country does not engage in the clothing industry and was not included in the analysis.

This study gathered historical data on the export trade value of clothing at the 2-digit Standard International Trade Classification (SITC) level from 2012 to 2018 from the United Nations Comtrade Database. In addition, the GDP data were acquired from the statistics database of the World Bank, and the geographical distance among countries was obtained from SeaRates, which is a search engine providing shipping rates.

3.2. Multiple Regression with Panel Data

For data analysis, we used the approach of panel data estimation aided with EViews – an econometric and statistical software. A pooled cross sectional (PCS) approach or cross sectional (CS) ordinary-least-square (OLS) regression is frequently adapted in the gravity trade model. Nevertheless, it has been argued that these approaches produce biased results (Cheng & Wall, 2005) since heterogeneity is not allowed in the error term for standard CS regression equations, which yields overstated results.

On the other hand, a panel estimation method highly will overcome these problems. Baltagi (2013) noted the advantages of using a panel data estimation method, which include the increase in informative data volume and data variation with less collinearity among the variables. This method also allows more efficiency and freedom degrees.

To extend an extensive analysis on the clothing trade, this study used panel data modeling estimation approach. The past investigations were only centered on the general commodity and not specific for apparel. The following analysis will provide insight into the main factors driving Asian clothing exports to the US market.

3.3. ANN Implementation and Configuration

This study developed the ANN with three layers consisting of input, hidden and output. The input layer comprises three input features (the GDPs of the exporter, the GDPs of the importer, and the distance between the exporter and importer), and one output (predicted clothing exports) in the output layer. To optimize neurons within the hidden layer (i.e., hidden neurons), we built various ANN with hidden nodes of 3 to 30 (see Figure 2). The ANN with its best predictive ability was identified through a comparison of the R^2 and RMSE of the training, validation and testing datasets across separate networks. As the study conducted by Dumor and Yao (2019), we used rectified linear units (ReLUs) as the activation function. To train the model, we used a stochastic gradient descent optimizer and MSE loss function.

Also, we applied K-fold cross-validation on the way to train and validate each ANN instead of the dataset segmentation into training and validation sets in solely one single step. The 2012–2017 dataset with 96 observations was separated into five groups (folds) of equal size at random. One group was applied as the hold-out or validation set, whereas the four remaining groups were used as the training sets. The model was fitted with the training set and the fitted model was used to make predictions on the validation set. This was processed fivefold. The means of the five R^2 and of the five RMSEs were calculated for each trained ANN tested by the 2018 dataset to predict the out-of-sample observations.

The training dataset was separated into 32 batches; each with a batch size of two. It was required 32 iterations to complete one epoch, which is a complete cycle of learning of the entire training dataset by an ANN. This study used 200 epochs to train each ANN at a learning rate of 0.01.

The values of exports, the GDPs of the exporter, the GDPs of the importer, and the distance were conformed to standards in the pre-processing stage. Thus, their mean values equal to zero and standard deviation values equal to one. For the proposed ANN implementation in Python, this study applied the Keras Sequential model. Then, we created and trained the ANN in a Jupyter notebook environment on Google platform.

4. Results

This section provides the key findings of interpretation, analysis and in-depth exploration of the reliable data this study acquired. This chapter begins with presenting and explaining the results of the multiple regression model. Finally, the results of ANNs are presented explaining their stronger predictive ability.

4.1. The Results of Multiple Regression Model

Table 1 shows the result of the panel data regression model. It indicates the pooled OLS model with an estimation

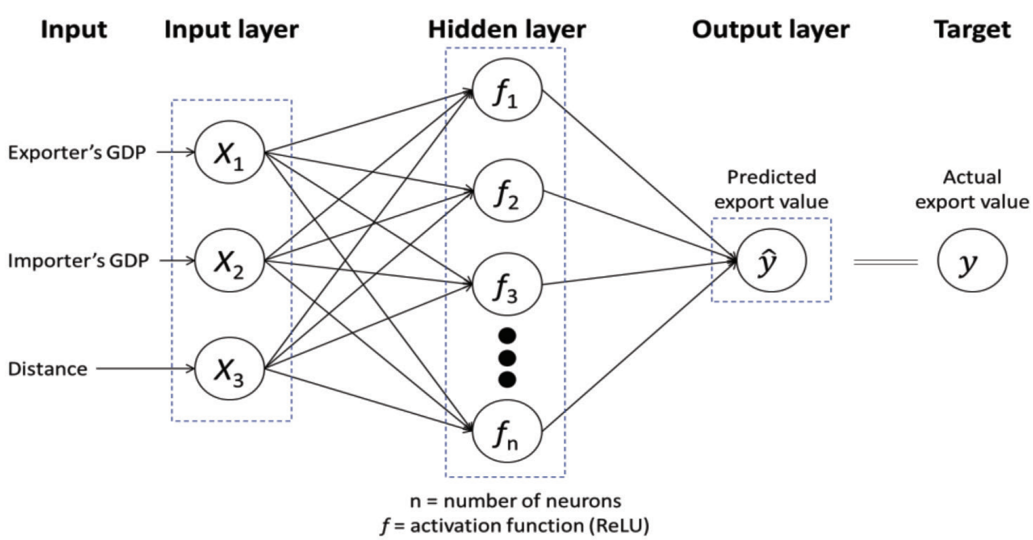

Figure 2: Structure of ANNs

of White's standard errors explained that 52.59% and 53.58% of the variance and the prediction errors (RMSE) of the US's clothing exports were 0.8788 and 0.8529 in the training and testing datasets, respectively.

The regression model shown below was a significant predictor of the clothing exports with $F\,(3,15) = 28.1$, $p < 0.001$.

$$\log(\text{Export}_{ijt}) = -2.9418 - 1.3165\log(\text{D}_{ij}) + 1.1675\log(\text{GDP}_{it}) + 1.5468\log(\text{GDP}_{jt}) \quad (4)$$

The three predictors significantly contributed to the model, as regression coefficients had a p-value smaller than 0.001. Unsurprisingly, the larger GDP of both exporter and importer contributed to higher bilateral clothing trade, while the distance between the exporter and importer hampered the bilateral clothing trade. As the fixed and random effects models did not yield better results, the pooled OLS model served as a reference for comparison with ANNs.

4.2. Results of ANNs

Table 2 shows that the mean values of R^2 and the RMSE expectedly increased and decreased respectively in the training and validation datasets, along with the increase in the number of neurons in the hidden layer, (i.e., hidden neurons). As they exceeded 25, however, the predictions became less accurate, as indicated by the decline in the R^2 values and increase in the RMSE values. The best model was when the ANN had 25 hidden neurons. This is evident when the best model was applied to predict the out-of-sample value of exports in 2017. Furthermore, that model attained an R^2 of 82.27% and RMSE of 0.4211 in the testing dataset.

The results above show that ANNs have a stronger predictive ability. In the in-sample predictions, the mean values of R^2 and the RMSE of the best ANN in the training or validation set are 75.4%/59.45% and 0.4895/0.5890, respectively. However, the regression model only attained an R^2 and RMSE of 52.59% and 0.8788, respectively. More importantly, in the out-of-sample predictions, the best ANN attained an R^2 of 82.27% and RMSE of 0.4211, whereas the regression model only attained an R^2 of 53.58% and RMSE of 0.8529.

Table 1: Results of Multiple Regression Model

R^2 (training)	0.5259
RMSE (training)	0.8788
R^2 (testing)	0.5358
RMSE (testing)	0.8529

5. Discussion

These results are encouraging on two fronts. First, unlike previous studies that built and assessed an extended gravity trade model with a relatively large number of predictors (e.g., eight in Dumor & Yao (2019) and seven in Wohl & Kennedy (2018)), this study examined the basic gravity trade model with only three conventional predictors. Meanwhile, some may argue that a model with more predictors provides higher predictive power, examining a basic, simple model could serve as a crude test of the predictive performance of ANNs. This study shows that high predictive performance can be achieved with as few relevant predictors as possible.

Second, dissimilar with previous studies employing a large dataset (e.g., 4536 observations in Dumor & Yao (2019) and 91,094 observations in Wohl & Kennedy (2018)), this study simply examined 96 observations for training and validation of the ANNs. Despite the limitations of the small population of datasets, this study has demonstrated that ANNs outperform linear regression models in predictive performance, and corroborate with the results of previous studies. Without a doubt, training ANNs with larger size datasets could deliver a better performance. In some

Table 2: Results of ANNs with Different Number of Hidden Neurons

	Number of Neurons in the Hidden Layer					
	3	**5**	**10**	**20**	**25**	**30**
Mean R^2 (training)	0.5939	0.6005	0.6881	0.7531	0.7540	0.7526
Mean R^2 (validation)	0.4384	0.4151	0.5499	0.6062	0.5945	0.5883
Mean RMSE (training)	0.6338	0.6289	0.5563	0.4921	0.4895	0.4903
Mean RMSE (validation)	0.6841	0.6918	0.6272	0.5749	0.5890	0.5881
R^2 (testing)	0.6346	0.6477	0.7839	0.8027	0.8227	0.7551
RMSE (testing)	0.6045	0.5936	0.4649	0.4441	0.4211	0.4949

situations, only a small size of datasets can be obtained due to various constraints and limited resources. However, the application of ANNs could achieve relatively higher predictive ability than conventional regression models.

6. Conclusion

This study applied a basic gravity trade model with the GDPs of the importing and exporting countries, and geographical distance between the two trading partners since the predictors of clothing trade from 16 South and Southeast Asian countries to the US market. Drawing upon the analysis of multiple regression and ANN, with a dataset of clothing export values recorded from 2012 to 2018, this study examined and compared the predictive power of these two research methods. The results showed that ANN outperformed multiple regression in predicting clothing exports of selected Asian emerging countries to the US market, with three predictors, including GDP of two trading countries and the physical distance between them.

Nevertheless, this study has the limitation of analyzing only conventional economic factors in the gravity trade model. Under the recent precarious global business environment, other determinants that bring uncertainty, for example, political stability and rights, trade protectionism, regional blocs and free trade agreement, trade facilitation factors, environmental and social sustainability, and dynamics which influent international trade of clothing should be considered in the future investigation.

In particular, the BRI, a perpetual strives with more infrastructure projects currently implemented in developing countries in Asia, could have a long-term effect on global trade patterns of clothing. The BRI partnering countries have the potential to incorporate foreign direct investment (FDI) in clothing manufacturing when business opportunities manage to arise.

To reduce labor costs, Chinese clothing companies have increased their FDI to the clothing industry in the BRI countries in the past few years. Some of these clothing companies have moved to BRI of South and Southeast Asia countries to anticipate lower production costs, e.g., from China to Bangladesh, Cambodia or Vietnam (Chan et al., 2019, Ho, Chan, Yip, & Tsang, 2020, Nong & Ho, 2019). More studies should focus on how the global trade of clothing would be transformed as the BRI unfolds over time.

Other factors such as the challenges of increasing production costs, unsettling geopolitics like the US-Sino trade war, and the rise in protectionism, which threatens global trade, have produced disrupting changes in the supply and production of clothing products. These changes could present an opportunity for emerging countries in Asia. Nevertheless, natural environment sustainability issues, such as energy consumption, fuel mix, carbon emission factors, should be addressed when developing countries intend to attract more FDI in order to grow their clothing sector for trade-led economic development. The impact of soft and hard trade facilitators, transport infrastructure and port establishment, on the global clothing supply chain's structure and operations should also be examined.

All these factors can be investigated, not only by the conventional approach of econometrics, but also by ANN. Future studies could explore the potential of using advanced neural networks or machine-learning methods to explore theoretical models that explain trade flows of international clothing at country and sectoral levels. Besides, researchers are advised to apply the basic gravity trade model as a baseline model for reference in evaluating the predictive ability of the extended models. This would help to assess the additional predictive power of more complex and comprehensive models.

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