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PERFORMANCE EVALUATION OF BILATERAL ECONOMIC COOPERATION BETWEEN TAIWAN AND PARTNER COUNTRIES UNDER NEW SOUTHBOUND POLICY: PAST, PRESENT, AND FUTURE

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Abstract. *Purpose* – in light of the Taiwan New Southbound Policy (NSP), this paper aims to evaluate the performance of bilateral cooperation between Taiwan and its economic partner countries in order to have a better understanding of the coherence of reciprocal relations in the past, present and future.

Research methodology – firstly, both individual forecasting models and combining forecasts were employed to predict the future values based on a period of thirty years (1990–2019). Secondly, the paper proposes non-convex DEA to detect non-convex characteristics of datasets where the volume of inputs and outputs were unevenly allocated in past years. Finally, a DEA window was applied to provide efficiency scores for decision-making units (DMUs) across a period of twelve years (2014–2025).

Findings – the results found that the efficiency of seven out of eight DMUs will improve in the coming years. With a stable performance in both scale and efficiency, Singapore is Taiwan's most successful economic partner, followed by Malaysia. The NSP remained as a vital foreign policy in supporting Taiwan's bilateral trade and outward foreign direct investment (OFDI).

Research limitations – more inputs and outputs are required in order to reflect the overall performance of the bilateral cooperation between two economies. Furthermore, more extended models are worth further investigation.

Practical implications – the forecasting values of exports and imports can be used in analysing Taiwan economy's trade deficits. This study provides useful inputs for managers in allocating resources of inbound and outbound values, and reacting rightfully to the uncertain future.

Originality/Value – the paper not only contribute much more than previous ones by evaluating into the relationship between size of scale and efficiency of bilateral economies but also provide advices for policymakers in creating mechanisms that can facilitate the NSP's sustainable development.

Keywords: Taiwan New Southbound Policy, data enveloping analysis (DEA), non-convex DEA, window DEA, forecasting models.

JEL Classification: F17, F21.

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Introduction

The rapid economic growth and geopolitical importance have made Southeast Asia (SEA) and India of the significant region to the global economy. Taiwan New Southbound Policy (NSP) promulgated in 2016 towards 18 countries in the Indo-Pacific region considered as the foreign policy with attempts to enhance the regional economic connectivity (Chang et al., 2017; Hsu, 2017; Huang, 2018; Lee & Sun, 2019; Yang & Chiang, 2019). Many researchers have studied on the core goals and implementation of the NSP, an interpretation emphasized on people-centered orientation. Hsu (2017) reviewed the differences between the new version and the previous "Go South" policy proposed under the Lee and Chen administration, the new core elements are added in attempting to reflect a cornerstone of the regional cooperation and integration, and to build the bilateral economies between Taiwan and its partnership. Chen (2020) argued that the NSP is an ambitious initiative that objectives are vague with lack of metrics to be evaluated. In the study of Lee and Sun (2019), economic roles of the five NSP "Flagship" agenda in endeavoring to promote the "Soft Power" for Taiwan and manufacturing capacity, and the ultimate objective is to gradually build up the win-win collaboration and a sense of regional community rather than the focus of economic-only policy. Chang et al. (2017) provided a comprehensive the review of short-and medium-term roadmap in order to potentially enhance values of cooperation targeting on six larger scale production countries (India, Indonesia, Thailand, Vietnam, Philippines and Malaysia), the paper suggests four major aspects of NSP should be focused on the collaboration of industry, market, capacity building and system.

The aforementioned literatures analyzed on socio-cultural and political aspects of the NSP phenomena, of which, few studies that focus on addressing the economic issues; thus far, none of prior researches provides empirical outcomes relative to the bilateral economic cooperation based on quantitative approaches. The wave of investment from Taiwan to the ASEAN have been increased gradually over the years; however, the uncertain suspicions and obstacles are remained, and needed to be further investigated (Chen, 2020). Therefore, this paper aims at evaluating the performance of bilateral cooperation between Taiwan and its partner countries based on the perspectives of the reciprocal relations. Many studies found effects of FDI of a country is correlated with its stage of economic development, and the relations between FDI and trade flows are substitution or complementary to each other (Lin et al., 2015; Kozlova & Miečinskienė, 2016; Ahmad et al., 2016; Bhasin & Baul, 2016; Camarero et al., 2018). Therefore, decision-making units (DMUs) are assumed as bilateral FDI and trade flows between Taiwan and its economic counterparts. In this paper, two inputs, Taiwan outward FDI (OFDI) and net import are capital outflow out of Taiwan considering as input cost; whereas, two outputs, Taiwan inward FDI (IFDI) and net export are output profit where Taiwan receives capital from its counterparts. The methodological approach is summarized in three main stages. Firstly, instead of using one single approach where it only deals with data trend under static condition, both individual and combining forecasts are utilized to produce accurate results. Five simple models are the mean method, moving average, exponential smoothing, theta and autoregressive integrated moving average (ARIMA) considered as the most fitted models by generating smallest errors within this study. Each dataset was performed in an out of sample forecast with a 6-step-ahead forecast. Secondly, a non-convex DEA was employed to provide scale-and cluster-adjusted scores (SAS) and scale efficiencies in the past period. Thirdly, the DEA window was applied to analysis inter-temporal empirical data and provide clear efficiency scores for 12 years (2014–2025). Therefore, this study contributes much more than previous ones by evaluating into the relationship between size of scale and efficiency of bilateral economies.

To our best knowledge, no prior study has employed an integrated approach of forecasting techniques, DEA non-convex and window analysis to evaluate the performance of DMUs. There are some limitations, which lead to the future research. In the light of Taiwan's NSP, there are 18 partner countries under its scope; however, due to the inadequate datasets, this article only examines the bilateral cooperation between Taiwan and the eight major targeting economies. Hence, it suggest that more economic indicators and powerful models are required in order to generate better fruitful results, and that provides a more comprehensive perspectives and advices for policymakers.

1. Literatures

1.1. The selection of forecasting models

Together with the rapid development of forecasting techniques, more innovative models can be used for increased forecasting accuracy of FDI, exports and imports. Since the approach of forecasts combination was firstly introduced by Bates and Granger (1969), an amount of papers have aimed at comparing the forecasting accuracy between individual and combining forecasts; however, no consensus in the conclusions (Ajayi, 2019; Thomson et al., 2019). A large number of literatures demonstrate that the accuracy of combining forecasts are not guaranteed to outperform the individual ones, but it is resulted in lower risk in practical prediction (Kourentzes et al., 2019; Alaminos et al., 2022). The accuracy of different techniques varies widely based on characteristics of datasets and the lengths of historical time series data (Çatık & Karaçuka, 2012; Petropoulos et al., 2018).

Between two individual economies, the trend of trade and investment are fluctuated largely on yearly basis and affected by many external factors. Hence, it is very difficult to predict the future data based on one single forecasting approach for 32 datasets with different characteristics and uncertain conditions. Fildes and Petropoulos (2015) proposed simple and accurate forecasting models that needs to be firstly considered, rather than using complex models, which are required to develop the formulation in computational challenges. Within a vast amount of models, it is important to select a feasible methodology that can be easily interpreted and consequently utilized to provide advices for policymakers. Therefore, both individual and combining forecasts are carried out carefully. The selection of models were decided which based on each dataset condition and the forecasting accuracy drawn from empirical results. To the best of the author's knowledge, none of the existing studies relative to the forecasts in bilateral foreign direct investment between two individual economies have been employed the proposed models as it used within this research. Therefore, this study aims at filling the gap in the forecast literature.

1.2. Data envelopment analysis and the selection of DEA models

Data envelopment analysis (DEA) was originally developed by Charnes et al. (1978), a non-parametric approach used in empirical studies for quantifying the efficiency level of DMUs. Recent years, a numerous amount of DEA models are available to evaluate the efficiency of DMUs in analyzing efficient scores of FDI and its impact on the economic growth for the host countries. Most of DEA models assume the efficient frontier is convex for the purpose on measuring efficiencies. However, non-convex frontiers are existed in the context of reality, and it cannot be solved by traditional methods (Bayaraa et al., 2019). Tone and Tsutsui (2015) introduced the non-convex DEA that regarded as the best model to deal with non-convex datasets; it is helpful in addressing the problem of imbalances between outbound and inbound investments.

In DEA approach, four available models aim at evaluating the performance of DMUs changes over time, including malmquist productivity index by Caves et al. (1982), dynamic DEA (Tone, 2010), resampling supper-SBM (Ouenniche & Tone, 2017); however, only DEA window analysis can provide the efficiency scores of single terms under the consideration of carry-over activities between multiple consecutive windows. The DEA window considers the problem of small amount of DMUs where only eight DMUs are analyzed under 12 adjacent years. Hence, both DEA non-convex and window model fit the aim of this study well. As far as the author's knowledge, there is non-existing literatures relatives to performance evaluation of bilateral economic cooperation based on using either non-convex DEA or window analysis.

2. Methodology

2.1. Forecasting techniques

This paper employs five simple forecasts are mean method, simple moving average, exponential smoothing, theta and ARIMA. Naïve model is known as Naïve NF1, together with auto ARIMA model, both are employed as forecasting benchmark.

In Naïve NF1 model, all forecasts performed by the value of the last observation (Athanasopolous et al., 2010). The equation is written as $\hat{y}_{T+h|T} = \hat{y}_T$, where $\hat{y}$ is the predicted value, T is the time and h is the horizon. Mean method is one of simple forecasting models, with the predictive values being equal to the average of historical data. The equation can be written as:

$$\hat{y}_{T+h|T} = \overline{y} = \left(y_1 + \ldots + y_T\right) / T, \tag{1}$$

Simple moving average (SMA) is considered as the simplest forecasting model (Svetunkov & Petropoulos, 2018). The sma() function of the package "smooth" constructs an autoregressive (AR) model in the single source of error state space form. The mathematical formulation is presented by:

$$\hat{y}_t = \frac{1}{k}\sum_{i=1}^{k} y_{t-i}, \tag{2}$$

where: y_t – actual value, t and k – length of the SMA. The AR(n) process is rewritten as:

$$y_t = w'v_{t-1} + \in_t,$$

$$v_t = Fv_{t-1} + g \in_t,$$

where $F = \begin{pmatrix} \frac{1}{k} & I_{n-1} \\ \vdots & \\ \frac{1}{k} & 0 \end{pmatrix}$, $g = \begin{pmatrix} \frac{1}{k} \\ \vdots \\ \frac{1}{k} \end{pmatrix}$, $w = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$, v_t is the state vector. (3)

Assimakopolous and Nikolopoulos (2000) developed theta model. The local curvature of time series through a coefficient theta ($\theta \in R$) is relevant to the second difference of data with formula as follow:

$$\nabla^2 Z_t(\theta) = \theta \nabla^2 Y_t, \ \ t = 3, \ldots, n, \tag{4}$$

where: $Y_1, \ldots, Y_n$ is the original time series and ∇ is the difference operator, as $\nabla X_t = X_t - X_{t-1}$.

Svetakov and Kourentzes (2018) developed the exponential smoothing, which employs the notion of potential information as an unobserved time series element. The model can deal with stationary and non-stationary in forecasting processes. The mathematical expression is as follow:

$$\hat{y}_{t+1} + i\hat{p}_{t+1} = (\alpha_0 + i\alpha_1)(y_t + ip_t) + (1 - \alpha_0 + i + i\alpha_1)(\hat{y}_t + i\hat{p}_t), \tag{5}$$

where $\hat{y}_t$ being the estimated value of time series, $\hat{p}_t$ is estimated values of the information potential and $\alpha_0 + i\alpha_1$ as complex smoothing parameters.

ARIMA is one of the most widely used forecasting methods, developed by Box and Jenkins (1976). It assumes a linear correlation of the time-series data in utilizing the observed linear dependencies, together with the aim to capture local patterns and extricate noise out of parameters. The non-seasonal ARIMA model is formula as:

$$y'_t = c + \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \tag{6}$$

where y'_t is the differenced series, p – order of autoregressive part, d – degree of differencing, and q – order of the moving average part.

The combination of individual forecasting methods employed to improve the forecast accuracy by hedging against forecast errors. The combined forecast is then obtained by:

$$\hat{y}_t = (f_t)'w, \tag{7}$$

where: y_t is the variable of interest, $f_t = (f_{1t}, \ldots, f_{Nt})'$, the simple average gives equal weights to all predictors $w = 1/N$, N is not perfectly collinear predictors.

2.2. Forecast evaluation

Thomakos and Guerard (2004) proposed the standard procedure of forecasts that it splits the time series into the training set and the test set. The test set should contain at least the same amount of data samples as the projected forecasting horizon h. In this study, the 80-20 split ratio is chosen; whereas, the 80 percent of initial 30 data points are applied to train the model, while the remaining 20 percent are used to compare actual values against forecasted ones. Evaluation metrics are used to compare the forecast accuracy of each proposed model against benchmark models obtained from the rwf() function (Naïve NF1) and auto.arima() function (ARIMA). Forecast errors are the difference between an observed value and its forecasts, which computed by:

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T}, \tag{8}$$

where the training data are given by $\{y_1, \dots y_T\}$ and the test data as by $\{y_{T+1}, y_{T+2}, \dots\}$. In this study, the mean absolute percentage error (MAPE) is used; this is one of the most popular error metrics in measuring forecast accuracy. The equation is written as follow:

$$p_t = \frac{100e_t}{y_t}. \tag{9}$$

If $y_t = 0$, errors will be infinite or undefined; if y_t is close to zero, errors are tended towards extreme values. The values of MAPE can be interpreted as follow: less than 10 percent considered as highly accurate forecasts; from 10 to 20 percent regarded as good forecasts; from 20 to 50 percent examined as reasonable forecast; and more than 50 percent denoted as inaccurate forecasts (Thomakos & Guerard, 2004).

2.3. Non-convex DEA

In order to determine S-shaped frontiers precisely, Tone and Tsutsui (2015) developed the non-convex DEA model aimed at identifying the influence of scale efficiency and clusters. With varying degrees of inputs or outputs, DMUs are divided into several clusters; hence, efficiency scores are localized rather than general scores attained from the entire group. The model proposes a scale-and cluster adjusted score (SAS) used to observe carefully DMUs which are not efficient. If the input-oriented are considered, the model can be described as follow:

The inputs and outputs data are formulated as:

$$X = (x_{ij}) \in \mathrm{IR}^{m \times n} \text{ and } Y = (y_{rj}) \in \mathrm{IR}^{s \times n}. \tag{10}$$

With m, s, and n are numbers of inputs, outputs and DMUs. It assumes that X and Y are positive values. The input-oriented estimates the effective performance of each DMUs in the constant returns to scale (CRS) and variable returns to scale (VRS) models are written as follow:

$$P_{\mathrm{CRS}} := \{(x, y) \mid x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\};$$

$$P_{\mathrm{VRS}} := \{(x, y) \mid x \geq X\lambda, y \leq Y\lambda, e\lambda = 1, \lambda \geq 0\}; \tag{11}$$

$$\theta_k^{\mathrm{VRS}} := \min_{\lambda, s^-, s^+} \left(1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{ik}}\right);$$

$$\text{s.t. } X\lambda + s^- = x_k, \ \mathbf{Y}\lambda - s^+ = y_k, e\lambda = 1, \ \lambda \geq 0, \ s^- \geq 0, \ s^+ \geq 0. \tag{12}$$

The scale efficiency (σ_k) of DMU are computed with the values from zero and one, a larger value that interprets the better efficient score.

The projection DMUs attained efficiency scores under the assumption that all SAS, CRS and VRS are efficient within its cluster. The SAS scores are formulated as:

$$\theta_k^{SAS} := 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{s}_{ik}^{-}}{x_{ik}} = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\left(1-\sigma_k\right)s_k^{cl-*} + s_k^{cl-*}}{x_{ik}}. \quad (13)$$

Where the SAS is not less than the VRS score:

$$\theta_k^{SAS} \geq \theta_k^{VRS}\left(\forall k\right). \quad (14)$$

If all DMUs are positioned in the same cluster, then $\theta_k^{SAS} = \theta_k^{VRS}\left(\forall k\right)$ indicating that there is no S-shaped frontiers with all DMUs located to the same cluster.

2.4. Window DEA

Banker et al. (1984) developed the window DEA that enables to provide the efficiency level of DMUs over the years under the consideration of carry-over activities between multiple windows. It increases the opportunities to realize on how efficiency level develops through sequences of overlapping window. This model estimates the efficiency change over time by using a moving average analogue that covers observations from whole study period; therefore, efficiency scores are more reliable. This model can be explained briefly as follow:

It assumes that N decision-making units (n = 1… N) are observed in T periods (t = 1… T), where r inputs used to generate s outputs. Therefore, the sample has N x T observations, and an observation n in period t, DMU_t^n has an r-dimensional input vector $\mathbf{x}_t^n = \left(x_{1t}^n, x_{2t}^n, \ldots, x_{rt}^n\right)'$ and one s-dimensional output vector.

$$y_t^n = \left(y_{1t}^n, y_{2t}^n, \ldots, y_{st}^n\right)'. \quad (15)$$

The window starting at the time k, $1 \leq k \leq T$ and with the width w, $1 \leq w \leq T - k$, is denoted by k_w. The matrix of inputs for this window analysis is written as:

$$X_{k_w} = \left(x_k^1, x_k^2, \ldots, x_k^N, x_{k+1}^1, x_{k+1}^2, \ldots, x_{k+1}^N, \ldots, x_{k+w}^1, x_{k+w}^2, \ldots, x_{k+w}^N\right); \quad (16)$$

$$Y_{k_w} = \left(y_k^1, y_k^2, \ldots, y_k^N, y_{k+1}^1, y_{k+1}^2, \ldots, y_{k+1}^N, \ldots, y_{k+w}^1, y_{k+w}^2, \ldots, y_{k+w}^N\right). \quad (17)$$

The matrix of outputs is as follow:

Lin et al. (2015) proposed that all DMUs in each window are compared and contrasted against from each other; hence, a narrow window width should be considered in order to provide more accurate outcomes that are efficient across the specific period.

3. Results and discussion

3.1. Data source

Given by aforementioned literatures, this paper defines the DMUs as bilateral trade and investment between Taiwan and its major economic counterparts. Since there are large differences among the amount values of OFDI between DMUs, eight DMUs classified into three clusters, are A, B and C which are considered carefully according to the scale of OFDI. Cluster A considers as two-way trade and investment between Taiwan and its partners, Singapore and Vietnam. Cluster B, which defines as DMUs between Taiwan and three partners are Australia, Thailand and Malaysia economies, respectively. DMUs in cluster C are between Taiwan and three member countries, are the Philippines, Indonesia and India, respectively. Table 1 shows the eight DMUs.

Table 1. List of eight bilateral economies (source: compiled by the author)

DMUs	Bilateral economic relation	Clusters	DMUs	Bilateral economic relation	Clusters
A1	Taiwan – Singapore	A	B3	Taiwan – Malaysia	B
A2	Taiwan – Vietnam	A	C1	Taiwan – Philippines	C
B1	Taiwan – Australia	B	C2	Taiwan – Indonesia	C
B2	Taiwan – Thailand	B	C3	Taiwan – India	C

The selection of target partner countries and the aggregate data are chosen which based on the consistent availability of Taiwan OFDI and IFDI data under the NSP. The minimum number of DMUs is at least twice of the total number of inputs and outputs which required by the DEA application. The raw data of Taiwan bilateral OFDI and IFDI are retrieved from the monthly report of Taiwan Ministry of Economic Affairs, whereas, the actual values of bilateral exports and imports are taken from the statistics database and Taiwan department of custom.

3.2. Data forecasting

This section aims to forecast the most accurate future values of 32 datasets for six years from 2020 to 2025. Statistical software "R" version 4.0.2, together with the additional packages of "forecast", "robets" and "smooth" are utilized to generate the forecasting results. Both individual and combining forecasts are examined carefully in order to select the best-fit models. In this study, an out of sample forecast is fundamental approach in the modelling process. Each sample set comprises of a period of 30 historical points are divided into a training set of the first 24 points and a validation set of remaining 6 points. As an initial step, the candidate forecasting models are selected for the training set. Consequently, a 6-step-ahead forecast used to predict future values and then compared them with the mean of the obtained ones against the previously generated validation set. MAPE is selected as a measure in evaluating which models are the best ones. It defines that the values of applied models are smaller than benchmark models, which are the random walk model (Naïve NF1) and auto ARIMA. Finally, the proposed methods found as the best-fitted models by providing the smallest errors occurred during the forecasting steps. The empirical results found that 14 out of 32 datasets using the forecast combinations are proved superior in comparison to the individual ones. The flowchart shown in Figure 1, which describes the forecasting procedures used in this research.

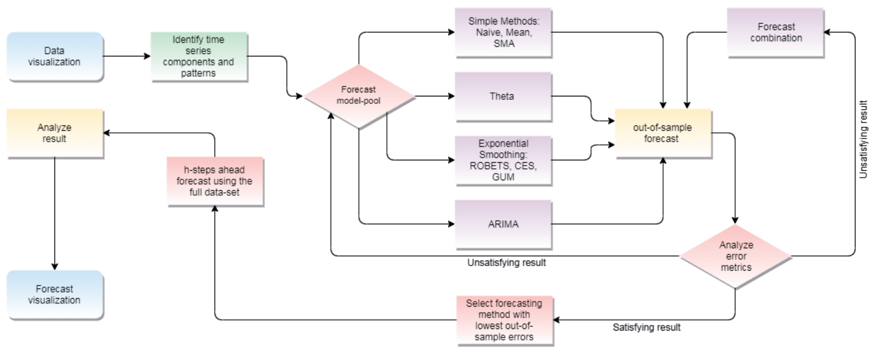

Figure 1. Forecasting flowchart

Table 2 shows the forecast accuracy of 32 datasets and comparisons between proposed models against benchmark models. The specific forecasting models and its predictive values of 32 datasets are also illustrated in Appendix. It found that this paper's applied models, which are used to predict the future values of imports, and exports regarded as the best-fitted models by providing the small errors ranged from 2.29 percent to 14.1 percent, representing the good to an excellent level of forecast accuracy. The empirical results found that six out of eight economic counterparts observe the uptrend tendency in exports and imports with Taiwan, only two-way trade with Indonesia and India experience the slight decrease in the coming years.

Table 2. The accuracy comparisons of forecasting models (source: compiled by the author)

MAPE/ export	A1	A2	B1	B2	B3	C1	C2	C3
Naïve NF1	11.61	11.9	17.85	12.75	31.53	19.44	36.88	9.34
Auto ARIMA	25.4	3.47	13.25	20.8	13.54	36.79	23.16	9.34
This paper's applied models	9.11	2.29	4.3	7.98	12.14	14.1	9.59	8.03
MAPE/ import	A1	A2	B1	B2	B3	C1	C2	C3
Naïve NF1	7.81	17.77	19.69	17.5	18.16	8.27	16.51	19.66
Auto ARIMA	7.39	16.47	40.18	13.25	14.3	13.01	24.71	19.66
This paper's applied models	7.25	9.86	6.67	8.23	8.06	8.2	8.6	8.75
MAPE/ OFDI	A1	A2	B1	B2	B3	C1	C2	C3
Naïve NF1	29.86	38.49	68.17	57.84	69.1	33.12	34.77	46.9
Auto ARIMA	35.73	34.79	49.53	35.93	69.2	46.03	34.29	57.1
This paper's applied models	24.3	28.03	24.31	28.81	23.9	25.2	22.29	24.7
MAPE/ IFDI	A1	A2	B1	B2	B3	C1	C2	C3
Naïve NF1	47.17	60.35	31.67	40.23	33.56	30.53	26.73	66.59
Auto ARIMA	37.53	48.00	26.95	37.63	29.93	36.53	35.79	23.34
This paper's applied models	27.59	22.3	26.47	25.88	21.68	24.83	16.2	19.78

Due to the large fluctuation of both inbound and outbound investment between two individual economies over a historical period, the MAPE values of OFDI and IFDI are ranged from the good to the reasonable level of forecast accuracy. Based on the indices of MAPE, it indicates the proposed models used in this study outperformed better than benchmark models, are Naïve NF1 and auto ARIMA. Taiwan's outward FDI to Vietnam, Thailand, India and Singapore will be remained as the constant uptrend for the forecasted period; it shows the sideways movement of investment from Taiwan to Australia, Indonesia and Malaysia, whereas, only Taiwan's OFDI to the Philippines will experience the fluctuation over the predicted period. The moving sideways forecasts of Taiwan's IFDI from India, Indonesia, the Philippines and Vietnam are found; whereas, it depicts a slight decrease trend in IFDI from Singapore and Malaysia; it foresees that Taiwan will receive more FDI from Australia, Thailand in the coming years.

The findings indicates the vital roles of the NSP in support of the increases in bilateral economic cooperation between economies. This is supported by the study of Kalirajan (2007) which found the significant role of regional foreign policy in attempts to facilitate Australia's bilateral trade volume with 17 member countries in the Indian Ocean Rim, Association for Regional Cooperation, increased by 15 percent in the period of 1999 to 2002.

3.3. Non-convex frontiers

In this research, the non-convex frontier model is used to detect the non-convex structure of datasets where an amount of inputs (OFDI and import) and outputs (IFDI and export) are unevenly allocated within a historical period. This study also makes comparisons across years to understand situation of each DMU compared to others. If SASs have larger values than scores given by VRS model, indicating non-convex characteristics of a dataset. Table 3 provides the average scores of all scale-and cluster-adjusted score (SASs), constant returns to scale (CRSs), variable returns to scale (VRSs) and scale efficiencyies change over the past six years (2014–2019). In cluster A, discrepancies between all scores are small, depicting the highest scores for each model, regarded as the most efficient when considering the adjusted score. The results show that large variations exist within cluster B, demonstrating the non-convex structure of economies. For cluster C, an average of SASs is centered equally between CRSs and VRSs, implying the existence of non-convex structure within the sample. Among three subgroups, an average score of scale efficiency in cluster A obtained at highest score of 0.9377, cluster B came in second with score of 0.8797, and the final ranking was DMUs in cluster C with much smaller score of 0.7565.

Table 3. Cross-period comparison between clusters (source: compiled by the author)

Cluster	SAS	CRS	VRS	Scale Eff.
A	0.9713529	0.9167085	0.9760838	0.9376754
B	0.8823381	0.7812942	0.8499074	0.8796777
C	0.7395895	0.6573728	0.8276483	0.7564878

Table 4 and Figure 2 present the average scores of all SASs, CRSs, VRSs and scale efficiencies in the historical period. Among eight DMUs, Singapore had the most substantial relationship with Taiwan in both values of trade and investment. Therefore, A1 achieved the best performance with all indicators of 1.00, interpreting an equality of two-way partnership. Like DMU1, C1 also ranked at the first place with a maximized efficiency of 1.00, explaining the reciprocal values of each other.

Table 4. Cross-period comparisons between DMUs (source: compiled by the author)

DMUs	A1	A2	B1	B2	B3	C1	C2	C3
SAS	1	0.94260	0.761217	0.89175	0.9940	1	0.3976	0.82613
CRS	1	0.83342	0.74170	0.62038	0.9817	1	0.2898	0.68991
VRS	1	0.95217	0.824533	0.72518	1	1	0.5369	0.96085
Scale Eff.	1	0.87535	0.8401	0.81715	0.9817	1	0.5568	0.70773

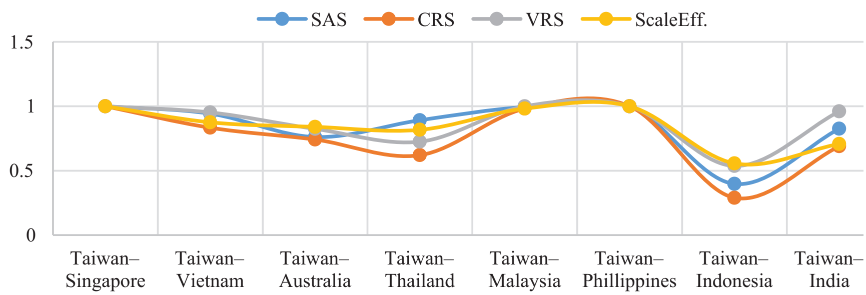

Figure 2. Cross-period comparisons between bilateral economies
(source: compiled by the author)

B1 followed in fourth by obtaining an average index of 0.84 in scale efficiency, with the SAS is placed between the CRS and VRS scores. The DMU outperformed in the years of 2015, 2016 and 2019 with all indices are scored at 1. However, B1 revealed to the non-convex structure in 2017 due to the smaller amount of an inward FDI.

The average score in scale efficiency of B2 ranked fifth, C3 followed in sixth, and C2 came in last. B2 was worsen, with four non-convex frontiers in historical years. C2 experienced three out of six observations are non-convex structures, with all indices are much smaller than other DMUs, from 30 to 50 percent.

Notwithstanding the fact that two-way economic cooperation of C3 is much smaller than DMUs; however, it experienced one non-convex structure only. Simultaneously with the remarkable score of 0.96 in VRS, indicating that India is regarded as the significant partner for Taiwan where the degree openness of the economic integration is proved in this study.

3.4. Window analysis

In the real context, the long-term strategy of trade and investment are a matter of great concern, macroeconomic issues at national level may take more than several years to adjust input factors given to the outputs level; hence, the chosen window length is five years. The results of 12 terms in inter-temporal analysis are conducted in Table 5 and Table 6, which show the efficiency trends of DMUs. It exhibits an average efficiency of 81.6 percent in a 12-year period (2014–2025) within the sample, 22 out of 92 observations are fully efficient. The forecasting years are projected to obtain an average score of 88.5 percent, increased by 13.9 percent compared to the historical term.

Table 5. Variation on performance across a period of 12 terms (source: compiled by the author)

Year / DMUs	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
A1	1	0.957	0.813	0.804	0.955	1	1	1	1	1	1	1
A2	0.910	0.878	0.824	0.896	0.824	0.600	0.682	0.677	0.681	0.668	0.661	0.654
B1	0.358	1	0.769	0.306	0.379	1	0.792	0.887	0.910	0.952	0.996	1
B2	0.480	0.521	0.771	0.476	0.673	0.665	0.999	0.999	0.999	1	1	1
B3	1	0.683	0.615	0.508	0.982	0.649	0.779	0.884	0.922	0.995	0.997	1
C1	1	1	0.975	0.972	0.936	0.998	1	1	0.987	0.988	1	1
C2	0.283	0.319	0.500	0.448	0.420	0.486	0.512	0.605	0.594	0.605	0.625	0.634
C3	0.851	1	1	0.785	0.623	0.930	0.924	0.946	0.966	0.970	1	0.997
Average	0.735	0.795	0.783	0.649	0.724	0.791	0.836	0.875	0.883	0.897	0.910	0.911

Table 6. Comparisons between the past and future period (source: compiled by the author)

DMUs	The past period	The forecasted period	Discrepancy	Average
A1	0.922	1	0.078	0.961
A2	0.822	0.671	–0.151	0.746
B1	0.635	0.923	0.288	0.779
B2	0.598	1	0.402	0.799
B3	0.74	0.929	0.189	0.835
C1	0.98	0.996	0.016	0.988
C2	0.409	0.596	0.187	0.503
C3	0.865	0.967	0.102	0.916
Av.	0.746	0.885	0.139	0.816

C1 obtained the most efficient observations over a time-span of 12 years with an average index of 98.8 percent, where the DMU found to have the lowest slacks between input and output variables. The two-way investment was ranked at fifth out of 8 DMUs, Taiwan export and import from its counterpart was at fourth and eighth, respectively. It is the small size in both inputs and outputs, but reflect the proportionality collaboration between Taiwan and the Philippines.

Singapore is Taiwan's largest trading partner. Recently, Singapore is the second destination of Taiwan OFDI, after Vietnam; Taiwan received the largest amount of investment from Singapore, with 40 percent out of the eight DMUs. A1 is the only counterpart attained fully efficient scores over seven consecutive years 2019–2025. Therefore, Singapore regarded as the most successful economic partner in the regional bloc in both size and efficiency.

C3 came in third with an average score of 91.6 percent; it predicts that it will be increased by 10.2 percent in the forecasted period. India is Taiwan's smallest FDI recipient compared to other NSP partner countries, with only 4 percent. However, as analyzed in the non-convex DEA assessment, this DMU obtained an impressive score of VRS in the historical years, exhibiting an acceleration of economic exchanges and stronger ties between two countries in efficiency.

Taiwan-Malaysian relation estimates to be risen by 18.9 percent in efficiency. Malaysia is Taiwan's second largest trading partner, after Singapore and the third largest investor in Taiwan market, after Singapore and Australia. It made an estimate of fully efficient in 2025 after a fluctuation in efficiency during a period 2014–2018. The result indicates the intensifying economic ties between two economies.

B2 ranked at fifth in efficiency. It exhibits the most improvement in efficiency by comparing the average score of forecasting and historical years, it expects to be risen sharply with 40.2 percent. Thailand is Taiwan's third largest FDI recipient in the regional bloc. Overall, the forecasting years are predicted to obtain the stable efficiency performance, with fluctuation around 77.9 to 100 percent.

Australia is the only country that Taiwan imports a greater value than it exports, with major merchandises are coal, iron ore, natural gas, copper and agricultural products. B1 ranked at six in efficiency. It revealed variations in efficiency in the past period, with fluctuation between 35.8 and 100 percent; however, it gradually increases in the forecasting period.

Vietnam has huge development opportunities to ride FDI waves from Taiwan. The finding shows that efficient scores experience the decrease almost 15.1 percent in the coming years after reaching the peak of 91 percent in the year of 2014, interpreting uneven utilizations between inputs and outputs, where values of OFDI are much greater than IFDI. Taiwan continues to increase the large amount of investment into Vietnam, not only light industries but also high tech factories.

C2 observed the lowest ranking, with an efficiency score at 50.3 percent, the fluctuation between 28.3 and 63.4 percent. Taiwan-Indonesia bilateral economy experienced the smallest scores in all indicators of SAS, CRS, VRS and scale efficiency. The empirical results interpret that Indonesia regarded as the smallest economic counterpart out of eight DMUs in both size and efficiency.

4. Discussion

The above empirical results depict that seven out of eight DMUs characterized by upward trends of efficiencies in the forecasted period (2020–2025), indicating the significant role of the NSP in support of Taiwan's exports, imports and outward FDI. Some previous studies had examined the regional economic cooperation between countries by measuring the impact of FDI and trade values on bilateral economies. Goh et al. (2013) found the correlation of two-way collaboration between Malaysia and 59 countries over the period from 1991 to 2009. The findings indicate the positive coefficients of IFDI for the bilateral imports and exports, whereas, the OFDI is negligible impact on the linkages for Malaysian's bilateral trade values. In the literature of Li et al. (2019), the authors investigates the performance evaluation of bilateral economic cooperation between China and 64 countries under the international trade of the Belt and Road Initiatives (BRI) over the period 2010–2017. The empirical results exhibited that 46 (72 percent) countries increased the trade volume with China in 2010–2017 period. This study is considered as novelty contribution to the BRI foreign policy for Chinese policymakers using the quantitative approach. In this paper, it aims to fill the gap by focusing more closely on performance evaluation of two-way (inbound and outbound) cooperation in order to identify the coherence of bilaterally reciprocal relations based on the past, present and the future data of bilateral FDI and trade in the light of Taiwan's NSP.

Conclusions

Based on the findings of an integrated approach, it considers in classifying DMUs into four groups. Group I, A1 and B3 shows a stable efficiency performance in terms of both scale and efficiency, characterized by increasing returns to scale (IRS), indicating Singapore is the most successful economic partner, followed by Malaysia. The result underpins the complementary nature of partnership between two economic alliances. Group II includes counterparts like Thailand, India and the Philippine, considered as Taiwan's small and medium-sized collaborations; however, the efficiency scores are found that relatively high, it suggests that Taiwan NSP policy makers should promote further agendas in order to attain the win-win cooperation for both sides. Group III, two-way economic cooperation between Taiwan and its partnership, Australia and Vietnam, viewing as large scale of input values but resulting in lower efficiency scores, indicating the decreasing returns to scale. The findings emphasize on the alleviation between capital outflows and inflows. Taiwan has slide towards increased merchandise trade deficit with Australia where imports are greater value than exports. Whereas, Taiwan OFDI to Vietnam has increased sharply but IFDI from Vietnam to Taiwan are stagnated, it caused to the low scores in performance. Group IV, the large uneven allocations of inputs and outputs are major causes of poor performance, bilateral economy between Taiwan and Indonesia regarded as small value in both size and efficiency.

This research differs from the existing literatures in three novel aspects. Firstly, the methodological contribution aims towards a framework in three major stages, which includes data forecasting, non-convex frontiers and window analysis in both dynamic and volatile macro-environment. Secondly, the predictive values of exports and imports can be used in analyzing Taiwan economy's trade deficits. It also solves the deficiency of forecasting literatures relating to investment flows, exports and imports between Taiwan and its economic counterparts.

Thirdly, this study provides useful inputs for policy makers in allocating resources of inbound and outbound values, and reacting rightfully to the uncertain future. The paper not only add to the literature by evaluating the performance of two-way economic cooperation, but also provide advices to policy makers in creating a mechanism design to pursuit the sustainable development and promoting the NSP agenda for its regional policy.

It is worth noting that the NSP considered as vital foreign policy where Taiwan inbound investment and export will be increased in the forecasted period. Taiwan government has pursued an active policy aimed at enhancing the NSP. Many factors may contribute to the level of scale inefficiencies such as outward sources are greater values than inwards, and the political environment change. Nevertheless, the outcomes may be due to the effects of long-term sustainable investments. It suggests that the policy makers should focus on persistent efficiency enhancement in the long-term. The promotion of scale efficiency change is a main key to increase the FDI attractiveness from its economic partnership. The NSP's member countries should focus on industrial restructuring, regional economic circle development and digital development in order to gain more investment from each other.

As the limitation of this study, it suggests more national economic indicators and efficient models, and its theoretical extensions are worthy of further examination in order to reflect the perspective of coherence of reciprocal relations between Taiwan and the 18 member countries in the light of the Taiwan's NSP.

Data availability statement

The data that support the findings of this study are available in Taiwan Ministry of Economic Affairs and Taiwan Customs Administration.

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APPENDIX

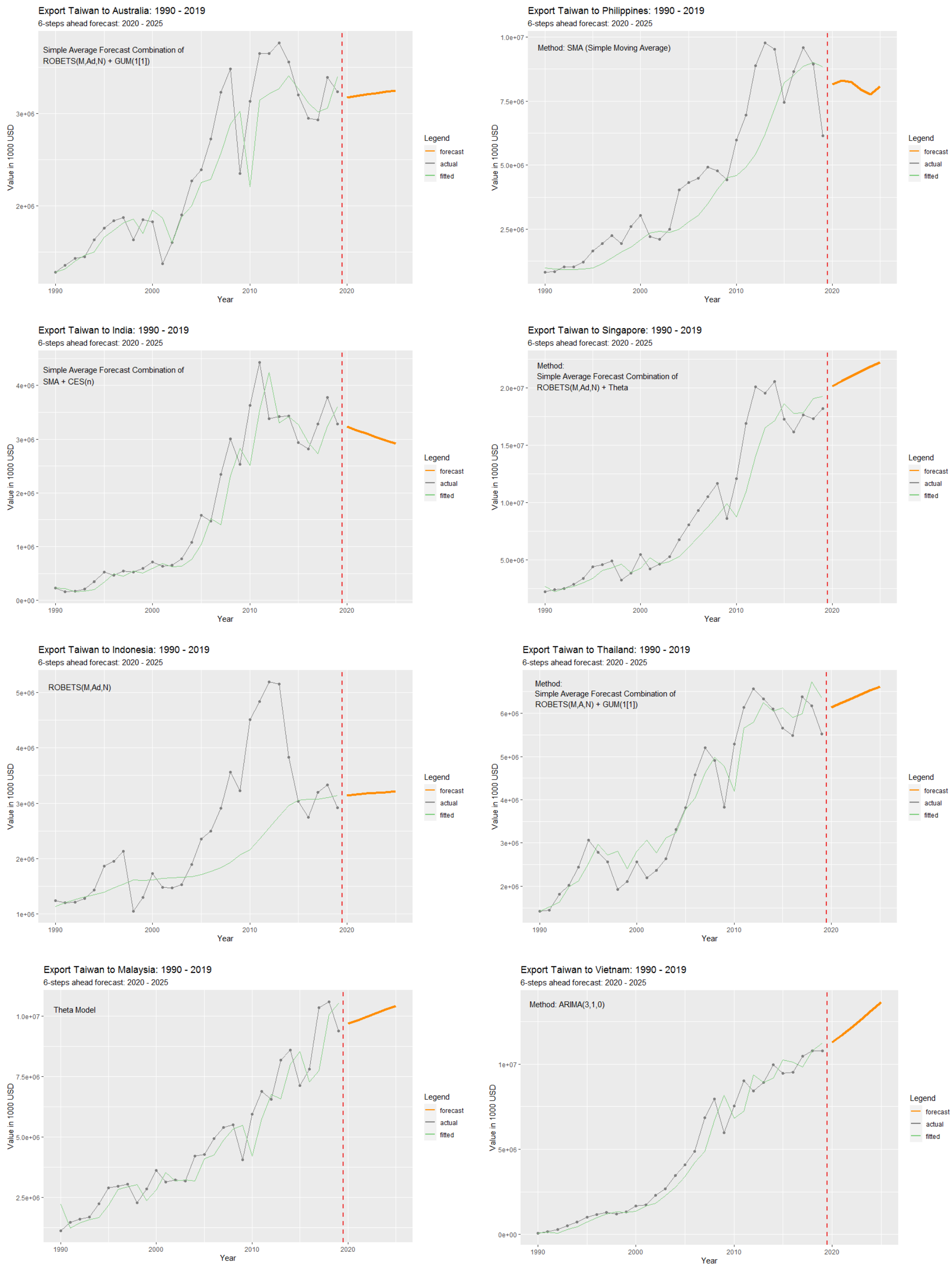

Figure A1. Export forecasts from Taiwan to eight NSP counterparts

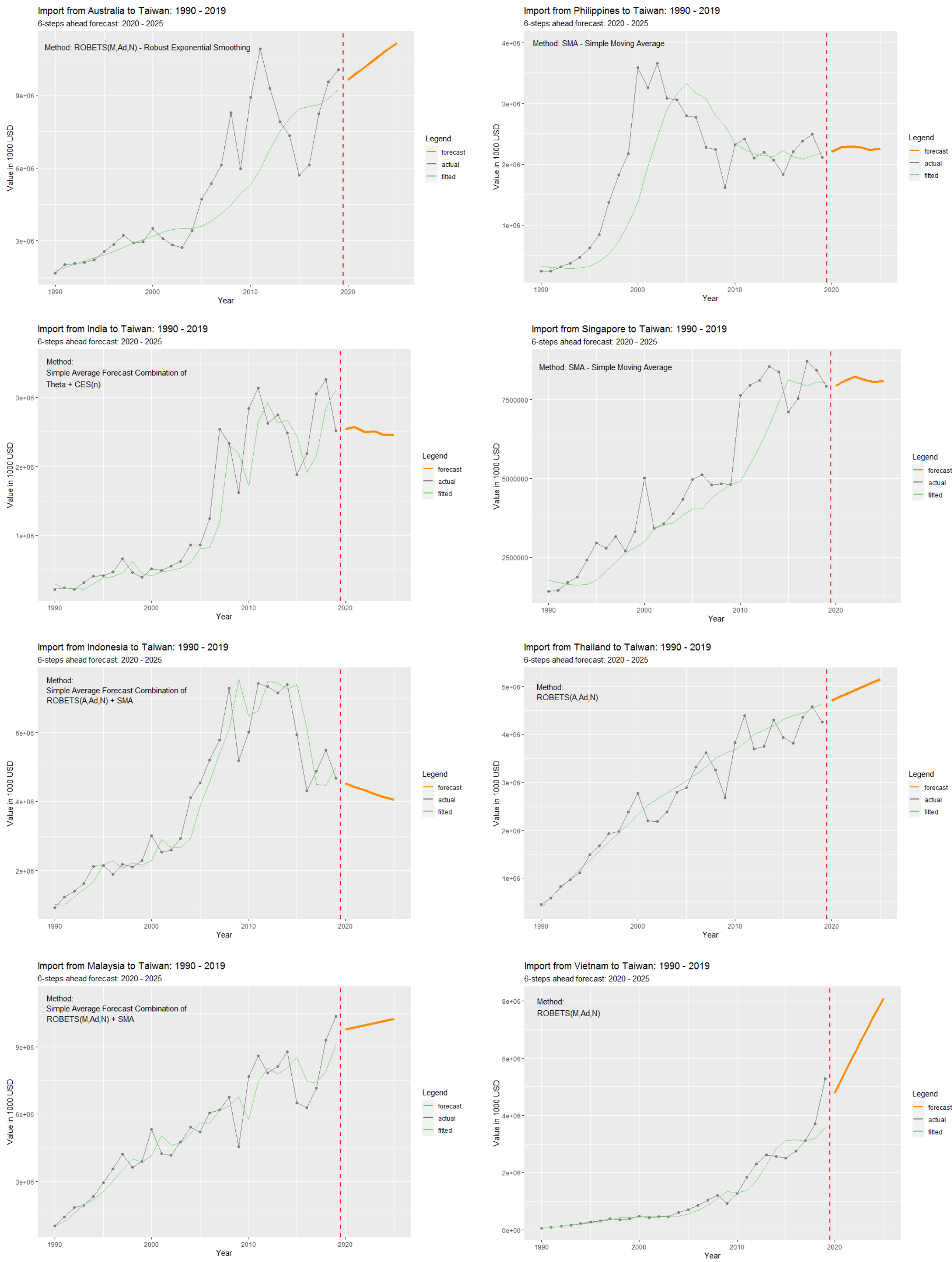

Figure A2. Import forecasts from eight NSP counterparts to Taiwan

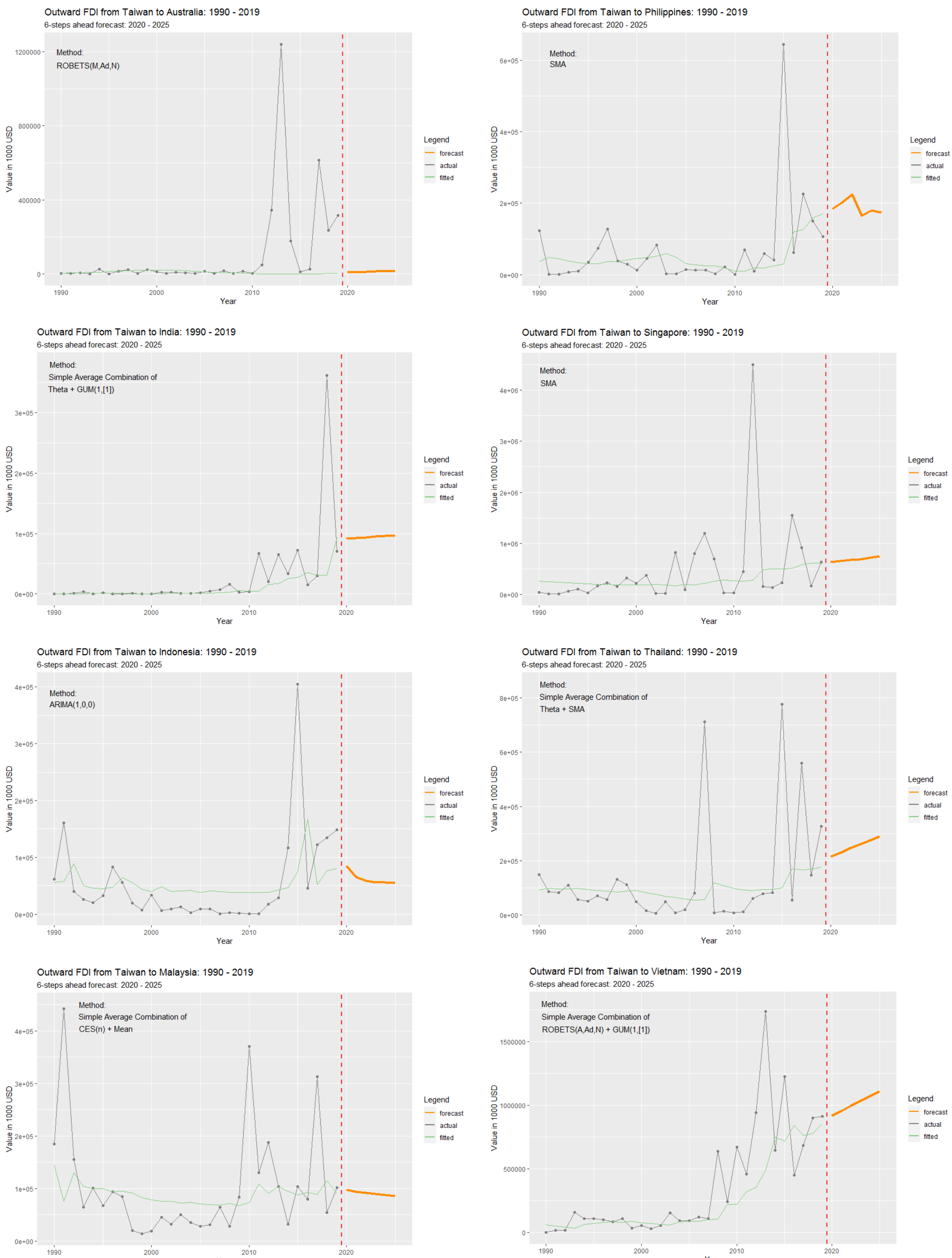

Figure A3. Outward FDI forecasts from Taiwan to eight NSP counterparts

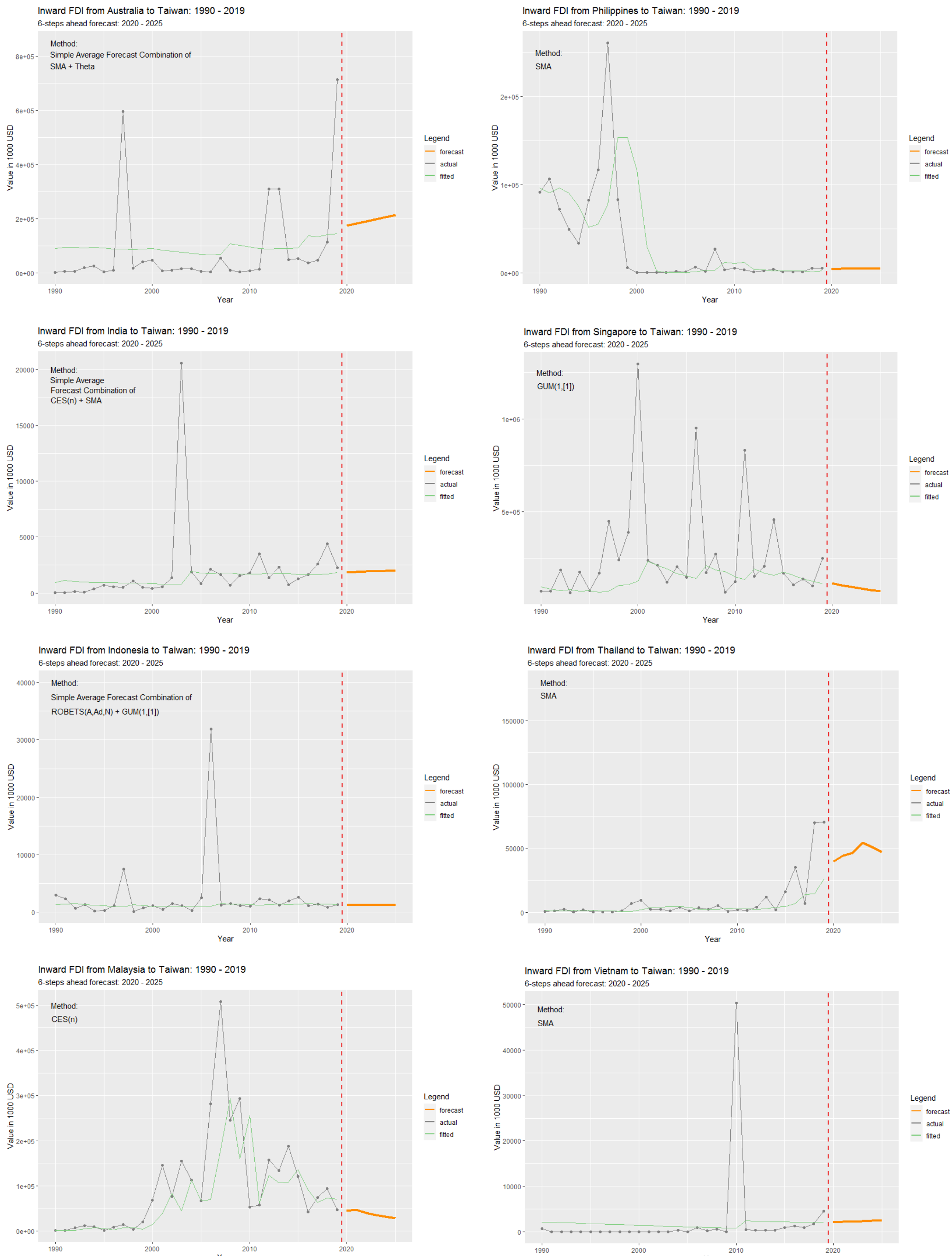

Figure A4. Inward FDI forecasts from eight NSP counterparts to Taiwan