Analysis of Trade and Technology Absorption in Thailand by Using Bvar and Msbvar Model

Juthathip Phoosaran[*1], Anuphak Saosaovaphak[2] and Chukiat Chaiboonsri[2]

[1]Master Student of Faculty of Economics, Chiang Mai University
[2]Faculty of Economics, Chiang Mai University
[*]Corresponding author, E-mail: juthathip.phh@gmail.com

Abstract

This research aims to find out the relationship between each variable of trade and technology absorption and to compare and forecast technology absorption in Thailand by using BVAR and MSBVAR models from 1995 to 2019. To achieved the paper's goals, the authors assumed that variables are both dependent and independent including gross domestic product per capita (GDP), degree of trade openness (DOT), human development index (HDI), and gross capital formation (CF). For technology absorption, the authors used three proxies to reflect trade and technology absorption, namely manufacturing value added (MVA), the value of high technology exports (TECHEX), and the value of charge for the use of intellectual property payment in the balance of payments (BOP). Consequently, the model was based on the VAR approach since each variable has an equation that explains its evolution based on its lags of the other model variable. Data have been collected from the World Bank and annual reports by government organizations. For analysis of our data, BVAR and MSBVAR were used in this studied. R and Eviews programs were used to estimate and display the result of this study. Our analysis showed that MSBVAR.lag3 is the most suitable to find out the relationship between each variable and to forecast the impact of technology absorption in Thailand.

Keywords: *Technology absorption, Bayesian Vector Autoregressive, Markov switching Bayesian Vector Autoregressive*

1. Introduction

There has been reported the important role of technology absorption and technological gap between developing countries. It is an important tool to increase productivity, raise competitiveness, driving down the cost of producing goods, and improving living standards around the world (Lynch, 2017). Moreover, Technology absorption has the characteristic high adaptability to the firm and center openness. Absorption in technology costs less, which allows technological followers to gain faster by importing and absorbing technology that was already done by the leader or developed countries (UNCTAD, 2003). Therefore, technology absorption is a sustainable process of technology evaluation, introduction and assimilation, transformation practice, and re-development. For Thailand, technology transformation plays an important role in the workforce market. There are many confusions that advanced technology will affect human work. Reskill is needed for existing labor (Startup Thailand, 2019). Consequently, the reason for this study concerns how the economic variables impact trade and technological absorption and realize which model is more suitable to predict and forecast trade and technology absorption in Thailand.

2. Objectives

1) To investigate the relationship between variables of technology absorption in Thailand
2) To compare technology absorption in Thailand by using BVAR and MSBVAR models

3. Materials and Methods

Theoretically, the business cycle is considered moving upward from depression phrase through recovery to appropriate phrase and back through the recession to depression once again. Technology shock is one of the factors that affect cyclical fluctuations. A quick technical change causes a boom while a slow technical change results in a recession (Gazda, 2010). Technical change pushes out the production possibility frontier, then raises the marginal product of both capital and labor. For Solow's model (1987), production depends on two factors namely capital input (K) and, labor input (L), and introduces technological growth as a function of production. Increasing technological progress leads to more productiveness. Without technological change, the only way to achieve this growth is through population growth, but then per capita income will not change in the long run. It explains why technology growth is important for output per capita to grow in the long run. Romer (2018) began constructing his endogenous growth theory. He demonstrated how a change in technology is different in ideas or knowledge accumulation to produce goods. This idea can be produced by capital and labor inputs. Besides, policies that different countries legislate are the key process to work for changing growth path. He needs to explicitly model the R&D process. Romer explains the rate of technological change, $A_{t+1} - A_t$ is determined by both current technology level, A_t and labor input, l_T^R working in the R&D sector. Therefore, population growth can be a source of growth in per capita income because more labor working in the R&D sector will generate the rate of technological change, and hence, the growth rate is high in equilibrium.

This study has gathered many theoretical foundations and literature reviews to be applied as a guideline in this study. The theoretical is presented below.

Bayesian Vector Autoregression (BVAR) model

Bayesian Vector Autoregression (BVAR) is an estimated vector autoregression. It is different from the standard VAR model. Parameters in the BVAR model are treated as a random variable with prior probability, rather than a fixed value.

A. Bayes' Theorem

Bayes' theorem expresses the conditional probability or posterior probability of an event A after B is observed in terms of the prior probability of A, the prior probability of B, and the conditional probability of B given A. Let $A_1, A_2, \ldots, A_k$, be events that partition in sample space, ω that do not happen at the same time. Therefore, $\bigcup_{i=1}^{n} A_i = \omega$. The conditional probability can be stated as $P(A_n|B) = \frac{P(A_n \cap B)}{P(B)}$.

Then, Bayes' theorem is described by:

$$P(A_n|B) = \frac{P(B|A_n)P(A_n)}{P(B)}. \quad (1)$$

B. Bayesian Inference

For analysis of Bayesian statistics, the parameter of the random variable, θ, or data that is not collected from observations, $\tilde{y}$ is $p(\theta|y)$ or $p(\tilde{y}|y)$. It can be concluded that y is a known variable, the probability of parameter θ is equal to the joint probability distribution between θ and y. This joint probability distribution or joint probability density function is consists of the sampling distribution, p(y| θ) and prior distribution, p(θ). More formally, the equation becomes: $p(\theta, y) = p(\theta)p(y|\theta) = p(y)p(\theta|y)$.

The predictive inference is processed by assigning a value of marginal distribution or prior predictive distribution of y: $p(y) = \int p(\theta)p(y|\theta)\mathrm{d}\theta$.

Therefore, forecasting the value of predictive inference, $\tilde{y}$ can be demonstrated as:

$$p(\tilde{y}|y) = \int p(\tilde{y}, \theta|y)\, p(\theta|y)\mathrm{d}\theta \quad (2)$$

C. Prior

The prior shows our prior beliefs. In the more general case, θ can take a finite number of values, 1,...,k. These values can be assigned with probabilities $p_1, \ldots, p_k$, which express our beliefs about θ before accessing to the data. The data y are assumed to be the observed value of a random variable Y.

The conditional density as follows:

$$p(\theta|y) = \frac{p(\theta)p(y|\theta)}{\int p(\theta)p(y|\theta)d\theta}. \quad (3)$$

The predictive inference is processed by assigning the value of marginal distribution or prior predictive distribution of y is follow

$$p(y) = \int p(y, \theta|u)d\theta \quad (4)$$

D. Likelihood function
The likelihood function is usually defined differently for discrete and continuous probability distributions. The way to obtaining this statement of the maximum of the likelihood function is known as maximum likelihood estimation by using the natural logarithm of the likelihood.
The function can be written as:

$$l(\theta|x) = f_\theta(x) \tag{5}$$

E. Posterior
Bayesian inference requires the determination of the posterior probability distribution of θ given the evidence X or can be written as p(θ|X). It was different from the likelihood function, which is the probability of the evidence given the parameters p(θ|X). Let a prior belief that the probability distribution function is p(θ) are observation x with the likelihood, p(θ|X).
Consequently, the posterior probability is defined as:

$$p(\theta|x) = \frac{p(x|\theta)}{p(x)} p(\theta). \tag{6}$$

The VAR(p) model can be written as:

$$y_t = c_1 + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \tag{7}$$

where,

y_t is an $M \times 1$ vector containing observation on M time series variables for t=1,…, T,
ε_t is an $M \times 1$ vector of errors,
c_1 is an $M \times 1$ vector of intercepts,
A_j is an $M \times M$ matrix of coefficients.

It is assumed that $\varepsilon_t^{iid} \sim N(0, \Sigma)$ and $A = (a, A_1, \ldots, A_p)'$
Therefore, it can be written in a simple VAR model as:

$$y_t = A' x_t + \varepsilon_t. \tag{8}$$

Markov Switching Vector Autoregressive
MSBVAR is a tool for economic modeling of univariate and multiple time-series data subject to shift in the regime. It is used to identify the possibility of a structural break in an unobserved regime.
According to Sims et al. (2008), the MS-BVAR model can be written as the follows:

$$y_y' A_0(s_t) = \sum_{i=1}^{\rho} y_{t-1}' A_i(s_t) + z_t' C(s_t) + \varepsilon_t' \theta^{-1}(s_t) \tag{9}$$

Where,

y_t is the M-dimensional column vector of endogenous
$A_0$is a non-singular $M \times M$ matrix,
$A_i(k)$ is a $M \times M$ matrix for 1≤ k ≤ h,
s_t is an n-dimensional shock process,
z_t is an indicator matrix taking the value1,
$C_t(s_t)$ is a $m \times n$ intercept matrix for 1≤ k ≤ h,
θ is an $m \times n$ diagonal matrix of factor loadings scaling the stochastic volatility factors on the vector of unobserved shocks ε_t.

This study has reviewed a few researchers that focus on trade and technology absorption. The details of each research are summarized and presented below. Tanna and Topaiboul (2005) investigated the causal links between human capital, openness through trade and FDI, and economic growth by using VECM. The result shows that trade openness leads to growth and FDI positive effect on human capital and influencing the future development of GDP. Itzhak, Lee, Goddard, and Smita (2010) identified globalization and technology absorption in Europe and Central Asia region. This paper states that trade, foreign direct investment, labor mobility are significant effects on technology absorption. Bittencourt (2013) studied technology absorption in the Brazilian industry. The result showed that research and development is the most effect on technology absorption, followed by trade and knowledge accumulation. Bannaga (2015) aims to investigate the relationship between trade liberalization and technology absorption in a less developing country (Sub-Saharan African). His finding suggests that human capital development and capital formation are highly associated with technology absorption. Świerczyńska and Kliber (2018) studied the relationship between the process of technology absorption, foreign direct investment, official development aid, and import. The result showed aid and import are more likely to affect technology absorption.

To achieve the objective trade and technology absorption are using BVAR and MSBVAR methods. The data for this study was collected from World Bank and other sources such as annual reports by the government organizations. In this study, all variables data were collected from 1995 to 2019, with a total of 25 observations. The data is annual and converted into the form of logarithmic return.

4. Results and Discussion

All data were converted into the form of logarithmic return, then it was essential to test a unit root before estimating the value with BVAR and MSBVAR. The unit root test is an important process because many time-series data often have non-stationary. Non-stationary data has mean and variance change when the time changes, which causes the relationship between the variables in the equation to have spurious regression that leads to the incorrect conclusion. In this study, three tests were used to warrant the high accuracy of the analysis process. The data that have trend and intercept were used in this study since they are more comprehensive than the models that have only either trend or intercept. For the ADF test, all variables are stationary. The ADF test statistic of BOP, CF, DOT, GDP, HDI, MVA and TECHEX were -5.442, -4.543, -5.952, -3.621, -4.039, -5.500, and -4.091, respectively. Therefore, all variables were stationary since the ADF test statistic was less than the Mackinnon Critical Value. The PP test results showed that all variables were stationary or integrated of order zero. The PP test statistic of BOP, CF, DOT, GDP, HDI, MVA, and TECHEX were -5.678, -4.664, -6.138, -3.620, -4.216, -5.729, and -4.285, respectively, which were less than the Mackinnon Critical Value. The DF-GLS was used to test the stationary. The results showed that the DF-GLF test statistic of BOP, CF, DOT, GDP, HDI, MVA, and TECHEX were -50678, -4.664, -6.138, -3.620, -4.216, -5.729, and -4.285, respectively, which were less than the ERS Critical Value.

Table 1 shows that BVAR.lag2 is the most appropriate model since its AIC statistic value is -29.17286, which is less than the AIC values of BVAR.lag0 and BVAR.lag1 models that are equal to -23.11732 and -24.09130, respectively. Next, the BIC statistic value of -23.98908 is less than the BIC values of BVAR.lag0 and BVAR.lag1 models that are equal to -22.77173 and -21.32662, respectively. Moreover, the HQC statistic value is -27.86916, which is less than the HQC values of the BVAR.lag0 and BVAR.lag1 models that are -22.77173 and -21.32662, respectively. Therefore, it was concluded that the BVAR.lag2 model, which has the lag length equal to 2, will have the most effects on the others variable.

Table 1 Lag length selection of BVAR model

Model	Lag	LogL	AIC	BIC	HQC
BVAR.lag0	0	272.8492	-23.11732	-22.77173	-23.03040
BVAR.lag1	1	333.0499	-24.09130	-21.32662	-23.39599
BVAR.lag2	2	440.4879	-29.17286*	-23.98908*	-27.86916*

Note: * indicates lag order selected by the criterion that gets the lowest log L, AIC, BIC, and HQC

According to Table 2, the Normal-Wishart obtained the lowest forecasting evaluation equal to 0.170815429. If the Root Mean Squared Error (RMSE) value is low, it means that the model is more suitable to use in forecasting than the model that gives a higher Root Mean Squared Error value. Next, the Mean Absolute Error (MAE) of a model concerning a test set is the mean of the absolute values of the individual prediction errors on overall instances in the test set, and Theil Inequality Coefficient (Theil) has the value between zero and one. If Theil' U statistic equals one, it means that the forecasting value is not accurate. Therefore, it should be decreased to smaller error, variance, and covariance. Therefore, the Normal-Wishart prior is the best prior for predicting trade and technology absorption in Thailand.

Table 2 Summary of Forecasting Evaluation by using 4 priors

Prior	Forecasting Evaluation Value
Litterman or Minnesota p	0.735828000
Normal-Wishart	0.170815429
Sims-Zha (Normal-Wishart)	0.246860048
Sims-Zha (Normal-Flat) prior	0.246344952

The BVAR.lag2 model for the forecasting results of variables BOP, CF, HDI, MVA, DOT, GDP, and TECHEX, respectively, are shown in Figure 1.

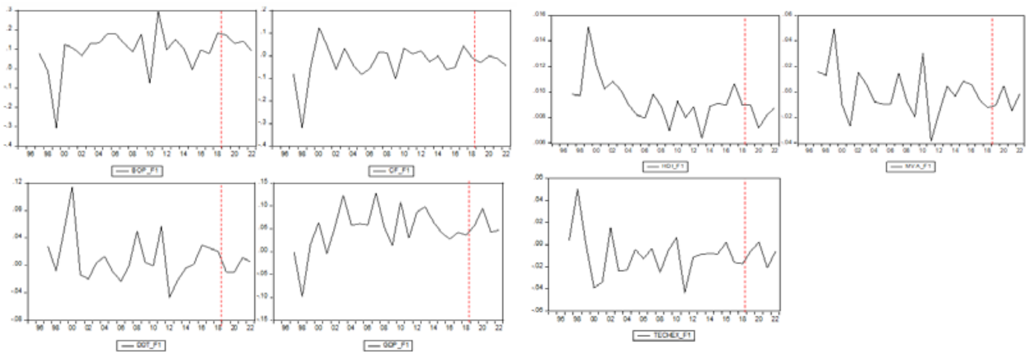

Figure 1 Forecasting results by BVAR.lag2 model

To analyze the appropriate lag length for the MSBVAR model in this study, three statistic values were used, namely AIC, BIC, and HQC.

According to Table 3, MSBVAR.lag3 is the most appropriate model in this study since its AIC statistic value is -336.636083, which is less than the AIC statistic values of MSBAR.lag1 and MSBVAR.lag2 models that are equal to -8.357753 and -14.941051, respectively. Besides, the BIC statistic value of MSBVAR.lag3 of -328.998786 is less than the BIC statistic values of MSBAR.lag1 and MSBVAR.lag2 models that are -5.580554 and -9.733803, respectively. Moreover, the HQC statistic value of MSBVAR.lag3 is -334.836966, which is less than the HQC statistic values of MSBAR.lag1 and MSBVAR.lag2 models that equal to -7.703528 and -13.714380, respectively. As a consequence, it was concluded that the MSBVAR.lag3 model, which has the lag length equal to 3, will have the most effect in this study.

Table 3 Lag length selection of MSBVAR model

Model	Lag	logL	AIC	BIC	HQC
MS-BVAR.lag1	1	-350.63608	-8.357753	-5.580554	-7.703528
MS-BVAR.lag2	2	-24.48651	-14.941051	-9.733803	-13.714380
MS-BVAR.lag3	3	-13.44866	-336.636083*	-328.998786*	-334.836966 *

Note: *The lowest statistic AIC, BIC, and HQC values

The forecasting evaluation can use three methods to evaluate the values and choose the best prior distributions. If the type has a low forecasting evaluation value, meaning that the model is more suitable to be used in this study. The three methods to evaluate are Normal-Wishart prior, Normal-flat prior, and Flat-flat prior. According to Table 4, Flat-Flat prior obtained the lowest prior, which the BIC statistic value is 35.5187, which is less than those of Normal-Wishart prior and Normal-flat prior models at 37.60203 and 37.53533, respectively.

Table 4 Prior comparison

Prior type	LogL	Number of parameters	Number of observation	BIC
Normal-Wishart prior	374.4693	8	25	37.60203
Normal-flat prior	362.188	8	25	37.53533
Flat- flat prior	132.138	8	25	35.5187*

Note: * The lowest BIC statistic value

Regime change from the flat-flat prior is illustrated in Table 5 and Figure 2. The data in this study were separated into two phrases, boom and down period as shown below.

Table 5 Regime Results from the flat-flat prior

Phase 1 : Boom	1998, 1999, 2005, 2008, 2009, 2011, 2014, 2015, 2016
Phase 2 : Down	1995, 1996, 1997, 2000, 2001, 2002, 2003, 2004, 2006, 2007, 2010, 2012, 2013, 2017

Source: Author's calculation (R program)

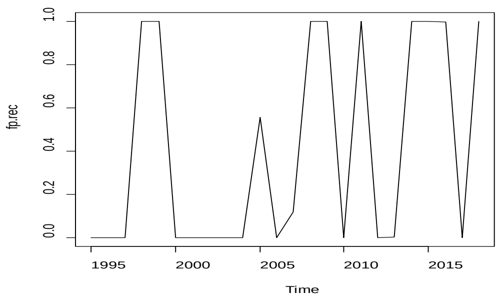

Figure 2 Regime Results from the flat-flat prior

The comparison between the values of Root Mean Squared Error (RMSE) and Theil Inequality Coefficient (Theil' U Statistic) was made to select an appropriate forecasting model between BVAR.lag2, MSBVAR.lag3 phrase1 and MSBVAR.lag3 phrase2 models. The RMSE was used to measure the differences between the values predicted and the values observed. The smaller the value, the better the model's performance. Theil Inequality Coefficient (Theil) is a tool used to measure the accuracy of the information, and Theil statistic has a value between zero and one. If Theil' U statistic is equal to one, it means that the forecasting value is not accurate. Therefore, it should be decreased to smaller error, variance, and covariance.

Table 6 The comparison of RMSE and Theil' U Statistic values between BVAR.lag2, MSBVAR.lag3 phrase1 and MSBVAR.lag3 phrase2 models

Variable	Model	RMSE	Theil' U Statistic
BOP_t	BVAR.lag2	0.1410	0.4949
	MSBVAR.lag3 phrase1	0.1340	0.5046
	MSBVAR.lag3 phrase2	0.1047*	0.3492**
CF_t	BVAR.lag2	0.1314	0.7232
	MSBVAR.lag3 phrase1	0.0662*	0.7580
	MSBVAR.lag3 phrase2	0.0968	0.7236**
DOT_t	BVAR.lag2	0.0704	0.7799
	MSBVAR.lag3 phrase1	0.0818	0.8864
	MSBVAR.lag3 phrase2	0.0582*	0.5457**
GDP_t	BVAR.lag2	0.0914	0.5353
	MSBVAR.lag3 phrase1	0.0525*	0.5511
	MSBVAR.lag3 phrase2	0.0924	0.4551**

HDI_t	BVAR.lag2	0.0043	0.2204
	MSBVAR.lag3 phrase1	0.0026*	0.1577**
	MSBVAR.lag3 phrase2	0.0051	0.2424
MVA_t	BVAR.lag2	0.0266	0.7937
	MSBVAR.lag3 phrase1	0.0222	0.4976**
	MSBVAR.lag3 phrase2	0.0207*	0.5194
$TECHEX_t$	BVAR.lag2	0.0503	0.7798
	MSBVAR.lag3 phrase1	0.0662	0.7580**
	MSBVAR.lag3 phrase2	0.0362*	0.7625

Note: * The lowest statistic RMSE values,
**The lowest statistic value Theil's U values

Table 6 illustrate MSBVAR.lag3 model gives more accurate and more precise forecasting results than the BVAR.lag2 model for all variables, which means the BOP, CF, DOT, GDP, HDI, MVA, and TECHEX variables that have a lag length equal to 3 will have the most impact on technology absorption in Thailand during the studied period since the RMSE and Theil' U statistic values of MSBVAR.lag3 model are lower than those BVAR.lag2 model for all variables. Therefore, the MSBVAR.lag3 model is used to forecast the impact of all variables on Technology absorption in Thailand.

From the appropriate model section, the MSBVAR.lag3 model is the most suitable. Consequently, the equation from the MSBVAR.lag3 model can be used to predict the relationship of each variable on trade and technology absorption in Thailand. The detail of each equation is explained as follows.

For MSBVAR.lag3 during prosperity phrase:

For BOP, the equation is used to analyst demonstrated as: $BOP_t = 0.0854 - 0.0166BOP_{t-1} + 0.0072CF_{t-1} - 0.0596DOT_{t-1} + 0.0294GDP_{t-1} + 1.2581HDI_{t-1} + 0.0150MVA_{t-1} + 0.0072TECHEX_{t-1}$.
Hence, the constant value is 0.0854 and other variables are set in a fixed equation system. The BOP variable of trade and technology at time t has a correlation with variables CF, GDP, HDI, MVA, and TECHEX at time $t-1$ in the same direction. It also has a correlation with variables BOP and DOT at time $t-1$ in the opposite direction.

For CF, the equation is used to analyst demonstrated as: $\mathrm{CF}_{t=} - 0.0140 + 0.0014\mathrm{BOP}_{t-1} - 0.0152\mathrm{CF}_{t-1} + 0.0395\mathrm{DOT}_{t-1} + 0.0112\mathrm{GDP}_{t-1} - 0.6403HDI_{t-1} + 0.0166MVA_{t-1} - 0.0152TECHEX_{t-1}$.
Thus, the constant value is -0.0140 and other variables are set in a fixed equation system. The CF variable of trade and technology at time t has a correlation with variables BOP, DOT, GDP, and MVA at time $t-1$ in the same. It also has a correlation with variables CF, HDI, and TECHEX at time $t-1$ in the opposite direction.

For DOT, the equation is used to analyst demonstrated as: $\mathrm{DOT}_{t=} - 0.0100 - 0.0080\mathrm{BOP}_{t-1} + 0.0069\mathrm{CF}_{t-1} - 0.0346\mathrm{DOT}_{t-1} - 0.0150\mathrm{GDP}_{t-1} + 1.4961\mathrm{HDI}_{t-1} + 0.0019MVA_{t-1} + 0.0069TECHEX_{t-1}$.
Therefore, the constant value is -0.0100 and other variables are set in a fixed equation system. The DOT variable of trade and technology at time t has a correlation with variables CF, HDI, MVA, and TECHEX at time $t-1$ in the same. It also has a correlation with variables BOP, DOT, and GDP at time $t-1$ in the opposite direction.

For GDP, the equation is used to analyst demonstrated as: $GDP_t = 0.0215 - 0.0112BOP_{t-1} + 0.0150CF_{t-1} - 0.0215DOT_{t-1} - 0.0022GDP_{t-1} + 1.1384HDI_{t-1} + 0.0706MVA_{t-1} + 0.0150TECHEX_{t-1}$.
Hence, the constant value is 0.0215 and other variables are set in a fixed equation system. The GDP variable of trade and technology at time t has a correlation with variables CF, HDI, MVA, and TECHEX at time $t-1$ in the same direction. It also has a correlation with variables BOP, DOT, and GDP at time $t-1$ in the opposite direction.

For HDI, the equation is used to analyst demonstrated as: $\mathrm{HDI_t} = 0.0079 - 0.0029\mathrm{BOP_{t-1}} + 0.0008\mathrm{CF_{t-1}}$ $-0.0010\mathrm{DOT_{t-1}} - 0.0004\mathrm{GDP_{t-1}} + 0.0287HDI_{t-1} + 0.0067MVA_{t-1} + 0.0008TECHEX_{t-1}$.
Therefore, the constant value is 0.0215 and other variables are set in a fixed equation system. The HDI variable of trade and technology at time t has a correlation with variables CF, HDI, MVA, and TECHEX at time $t-1$ in the same direction. It also has a correlation with variables BOP, DOT, and GDP at time $t-1$ in the opposite direction.

For MVA, the equation is used to analyst demonstrated as: $\mathrm{MVA_t} = -0.0197 - 0.0043\mathrm{BOP_{t-1}} - 0.0087\mathrm{CF_{t-1}}$ $+0.0125\mathrm{DOT_{t-1}} + 0.0080\mathrm{GDP_{t-1}} + 0.3866HDI_{t-1} + 0.0249MVA_{t-1} - 0.0087TECHEX_{t-1}$.
The result shows the constant value is 0.0197 and other variables are set in a fixed equation system. The MVA variable of trade and technology at time t has a correlation with variables DOT, GDP, HDI, and MVA at time t-1 in the same. It also has a correlation with variables BOP, CF, and TECHEX at time t-1 in the opposite direction.

For the relationship between variable $TECHEX_t$ and other variables at time $t-1$ can be explained in an equation as: $\mathrm{TECHEX_t} = -0.0140 + 0.0014\mathrm{BOP_{t-1}} - 0.0015CF_{t-1} + 0.0395\mathrm{DOT_{t-1}} + 0.0112\mathrm{GDP_{t-1}}$ $-0.6403HDI_{t-1} + 0.0166MVA_{t-1} - 0.0152TECHEX_{t-1}$.
This study illustrates the constant value is -0.0140 and other variables are set in a fixed equation system. The TECHEX variable of trade and technology at time t has a correlation with variables BOP, DOT, GDP, and MVA at time t-1 in the same direction. It also has a correlation with variables CF, HDI, and TECHEX at time t-1 in the opposite direction.

The forecasting results of variables BOP, CF, HDI, MVA, DOT, GDP, and TECHEX, respectively are shown in Figure 3. Considering, CF and TECHEX are impacts on trade and technology absorption while BOP, HDI, MVA, DOT, and GDP are negative impacts. However, all variables are backward to a stable point in the next eight periods.

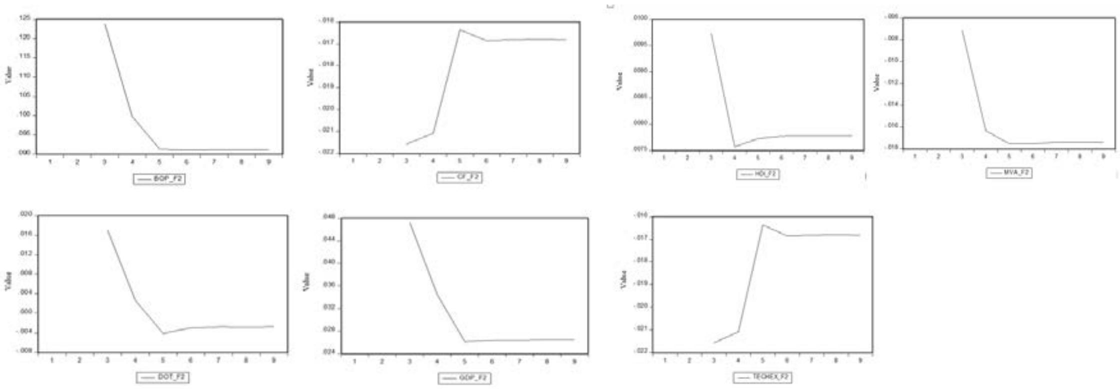

Figure 3 Forecasting results by MSBVAR.lag3 phrase1 model

For MSBVAR.lag3 during depression phrase:
For BOP, the equation is used to analyst demonstrated as: $BOP_t = 0.0854 - 0.0242BOP_{t-1} + 0.0179CF_{t-1}$ $+0.0117DOT_{t-1} - 0.0255GDP_{t-1} - 0.1320HDI_{t-1}$
$+0.2061 + 0.0265TECHEX_{t-1}$.
Hence, the constant value is 0.1353 and other variables are set in a fixed equation system. The BOP variable of trade and technology at time t has a correlation with variables CF, DOT, MVA, and TECHEX at time t-1 in the same. It also has a correlation with variables BOP, GDP, and HDI at time t-1 in the opposite direction.

Proceedings of RSU International Research Conference (2021)

For CF, the equation is used to analyst demonstrated as: $\mathrm{CF}_{t=}0.0184 + 0.0086\mathrm{BOP}_{t-1} - 0.0284\mathrm{CF}_{t-1} + 0.0348\mathrm{DOT}_{t-1} - 0.0053\mathrm{GDP}_{t-1} - 0.3829HDI_{t-1} + 0.2962MVA_{t-1} - 0.1538TECHEX_{t-1}$.
Therefore, the constant value is 0.0184 and other variables are set in a fixed equation system. The CF variable of trade and technology at time t has a correlation with variables BOP, DOT, and MVA at time $t-1$ in the same direction. It also has a correlation with variables CF, GDP, HDI, and TECHEX at time $t-1$ in the opposite direction.

For DOT, the equation is used to analyst demonstrated as:$\mathrm{DOT}_{t=}0.0259 + 0.0239\mathrm{BOP}_{t-1} - 0.0422\mathrm{CF}_{t-1} + 0.0027\mathrm{DOT}_{t-1} - 0.0268\mathrm{GDP}_{t-1} + 0.2283\mathrm{HDI}_{t-1} + 0.0536MVA_{t-1} + 0.1554TECHEX_{t-1}$.
The result shows the constant value is 0.0259 and other variables are set in a fixed equation system. The DOT variable of trade and technology at time t has a correlation with variables BOP, DOT, HDI, MVA, and TECHEX at time $t-1$ in the same direction. It also has a correlation with CF and GDP at time $t-1$ in the opposite.

For GDP, the equation is used to analyst demonstrated as: $GDP_t = 0.0781 - 0.0171BOP_{t-1} - 0.0215CF_{t-1} - 0.0366DOT_{t-1} + 0.0490GDP_{t-1} + 0.0680HDI_{t-1} + 0.1224MVA_{t-1} - 0.3341TECHEX_{t-1}$.
Consequently, the constant value is 0.0718 and other variables are set in a fixed equation system. The GDP variable of trade and technology at time t has a correlation with variables GDP, HDI, and MVA at time $t-1$ in the same direction. It also has a correlation with variables BOP, CF, DOT, and TECHEX at time $t-1$ in the opposite direction.

For HDI, the equation is used to analyst demonstrated as: $\mathrm{HDI}_t = 0.0095 + 0.0010\mathrm{BOP}_{t-1} - 0.0024\mathrm{CF}_{t-1} + 0.0010\mathrm{DOT}_{t-1} - 0.0010\mathrm{GDP}_{t-1} + 0.0327HDI_{t-1} - 0.0069MVA_{t-1} + 0.0004TECHEX_{t-1}$.
Thus, the constant value is 0.0095 and other variables are set in a fixed equation system. The HDI variable of trade and technology at time t has a correlation with variables BOP, DOT, HDI, and TECHEX at time $t-1$ in the same direction. It also has a correlation with variables CF, GDP, and MVA at time $t-1$ in the opposite direction.

For MVA, the equation is used to analyst demonstrated as: $\mathrm{MVA}_t = 0.0124 - 0.0041\mathrm{BOP}_{t-1} - 0.0011\mathrm{CF}_{t-1} - 0.0151\mathrm{DOT}_{t-1} + 0.0093\mathrm{GDP}_{t-1} + 0.2233HDI_{t-1} - 0.0145MVA_{t-1} - 0.0011TECHEX_{t-1}$.
Therefore, the constant value is 0.0124 and other variables are set in a fixed equation system. The MVA variable of trade and technology at time t has a correlation with variables GDP, HDI, and TECHEX at time t-1 in the same direction. It also has a correlation with variables BOP, CF, DOT, and MVA at time t-1 in the opposite direction.

For the relationship between variable $TECHEX_t$ and other variables at time $t-1$ can be explained in an equation as: $\mathrm{TECHEX}_t = -0.0034 + 0.0065\mathrm{BOP}_{t-1} - 0.0122CF_{t-1} + 0.0149\mathrm{DOT}_{t-1} - 0.0049\mathrm{GDP}_{t-1} - 0.2682HDI_{t-1} - 0.0937MVA_{t-1} + 0.0493TECHEX_{t-1}$.
Hence, the constant value is -0.0034 and other variables are set in a fixed equation system. The TECHEX variable of trade and technology at time t has a correlation with variables BOP, DOT, and TECHEX at time t-1 in the same direction. It also has a correlation with variables CF, GDP, HDI, and MVA at time t-1 in the opposite direction.

The forecasting results of variables BOP, CF, HDI, MVA, DOT, GDP, and TECHEX, respectively are shown in Figure 4. Considering, BOP, CF and GDP have a significant impact on trade and technology absorption while HDI, MVA, DOT, and TECHEX have a negative impact on trade and technology absorption. However, all variables are backward to equilibrium in the next seven periods.

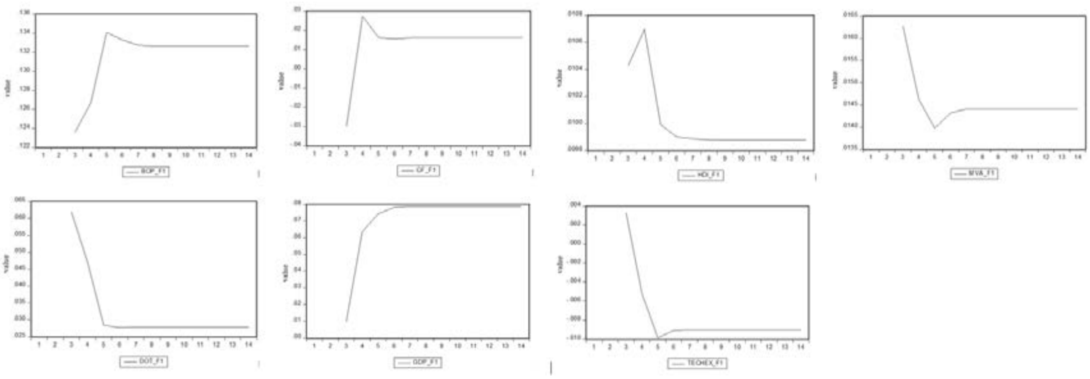

Figure 4 Forecasting results by MSBVAR.lag3 phrase2 model

5. Conclusion

The research paper on trade and technology absorption consists of two main objectives. Firstly, this study aims to investigate the relationship of each variable on trade and technology absorption in Thailand. Secondly, our objective is to compare and forecast technology absorption in Thailand by using BVAR and MSBVAR models. This study employed time-series data that have a total observation of 25 years from 1995 to 2019. All variables are assumed to be both exogenous and endogenous. Although the data is converted to logarithmic return, the result might be more accurate if the data were collected monthly. However, the parameters in BVAR are treated as random variables with prior probability, rather than a fixed value. Then, the BVAR model is an important tool to deal with the number of observation problems.

To an analyst in this study, BVAR and MSBVAR were used as the essential methods. All time-series data used in this study need to test the unit root. The result shows that all time-series data are stationary through ADF, PP, and DF-GLS statistic tests. The data that have both trend and intercept was used in this study since they are more comprehensive than the model that has only either trend or intercept. The results of BVAR showed that BVAR.lag2 is the most appropriate model due to the lowest AIC, BIC, and HQC statistic value. Besides, Normal-Wishart prior is the best prior used to predict trade and technology absorption in Thailand because gets the lowest RMSE, MAE, and Theil' U statistic value. For analysis of MSBVAR, the data are separated into two phrases, high and low regime. The result of lag length that is appropriate in this study is MSBVAR.lag3. Then, flat-flat prior gets the lowest BIC statistic value. Next, regime change from flat-flat prior are separated, MSBVAR.lag3 phrase1 and MSBVAR.lag3 phrase2.

Regarding the empirical result illustrated, the MSBVAR.lag3 model gives more accurate and more precise forecasting results than the BVAR.lag2 model for all variables because the RMSE and Theil' U statistic values of the MSBVAR.lag3 model is lowest. Therefore, the MSBVAR.lag3 model was used to forecast the impact of all variables on Trade and Technology absorption in Thailand. The relationship between each variable is considering two phrases, MSBVAR.lag3 phrase1 and MSBVAR.lag3 phrase2. For phrase 1 (prosperity), BOP, GDP, and HDI are the most impacts on trade and technology in Thailand while CF, DOT, MVA, and TECHEX are negative impacts. For phrase 2 (depression) BOP, CF, DOT, GDP, HDI, and MVA are the most impact while TECHEX is a negative impact on trade and technology absorption in Thailand.

6. Acknowledgements

I would like to express my deepest appreciation to Asst. Prof. Dr. Anuphak Saosaovaphak and Assoc. Prof. Dr. Chukiat Chaiboosri for support of my thesis, for his valuable advice, helpful contributions, practical suggestions, knowledge, and profound belief in my work. Without their assistance in every step throughout the process, this research would have never been accomplished.

7. References

Bannaga, A. (2015). Trade liberalization and Technology Absorption in a less developing country context.

Emerald Group Publishing, *14*(2), 149-170.
Bittencourt, P.F. (2013). An empirical analysis of technology absorption capacity of the Brazilian industry. *CEPAL review*, 1-17.
Gazda, J. (2010). Real Business Cycle Theory-Methodology and Tools. *Economics Sociology, 3*(1), 1-7.
Itzhak, G., Lee, B., Goddard, J. and Smita, K. (2011). Globalization and Technology Absorption. *The World Bank, 21*, 1-4.
Świerczyńska, K., & Kliber, A. (2018). Foreign technology absorption in Sub-Saharan Africa: A long-term analysis of the nature and stability of relationships. *Business and Economics Research Journal, 9*(3), 463-479.
Lynch, K. (2017). WTO Report Analyzes Link between International Trade and Technology. [Online]. Retrieved June 22, 2019, from https://www.americanexpress.com/us/foreign-exchange/articles/link-between-international-trade-and-technology/
Romer, M.P. (2018). Technological innovations into long-run macroeconomic analysis. *The Royal Swedish Academy of Sciences*, 14-20.
Sims, C. A., Waggoner, D. F., & Zha, T. (2008). Methods for Inference in large multiple-equation Markov-switching models. *Journal of Econometrics*, *146*(2), 255–274.
Solow, M. (1987). A contribution to the theory of economics growth, *Massachusetts Institution of Technology*, 2-4.
Start-up Thailand. (2019). Industrial 4.0 in Thailand manufacturing. [Online]. Retrieved September 29, 2019, from https://www.startupthailand.org/en/industry-4-0-set-to-add-50bn-in-thailands-manufacturing/.
Tanna, S. & Topaibou, K. (2005). Human Capital, Trade, FDI and ecomomic growth in Thailand. DEGIT Conference Papers, 1-28.
United Nations Conference on Trade and Development (UNCTD). (2003). Investment and Technology Policy for competitiveness, Technology for Development Series, 13-15.