EARLY WARNING SYSTEM FOR REAL ECONOMY: A CASE STUDY OF THAILAND

Jeerawadee Pumjaroen

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Applied Statistics)

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A CASE STUDY OF THAILAND
Jeerawadee Pumjaroen
School of Applied Statistics

.... Major Advisor
(Assistant Professor Preecha Vichitthamaros, Ph.D.)

The Examining Committee Approved This Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Applied Statistics).

.... Committee Chairperson
(Associate Professor Duanpen Theerawanviwat, Ph.D.)

.... Committee
(Associate Professor Yuthana Sethapramote, Ph.D.)

.... Committee
(Assistant Professor Preecha Vichitthamaros, Ph.D.)

.... Committee
(Assistant Professor Ramidha Srihera, Ph.D.)

.... Dean
(Assistant Professor Pramote Luenam, Ph.D.)

______/______/______

ABSTRACT

Title of Dissertation	EARLY WARNING SYSTEM FOR REAL ECONOMY:A CASE STUDY OF THAILAND
Author	Jeerawadee Pumjaroen
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The research aims to identify Composite Leading Indexes (CLIs) and develops the Early Warning System (EWS) by Partial Least Squares Structural Equation Modeling (PLS-SEM). The objective of EWS is to forecast the Economic Cycle (EC) in short-term, medium-term, and long-term periods.

Data from Thailand during Q1/2003-Q4/2008 are applied to pursue the purposes. The research uses Real Gross Domestic Product (GDP) as a proxy for the Thai economy, which is the target variable that EWS aims to early signal. The indicators from various economic sectors are gathered to construct CLIs. Before starting the estimation process, the data are filtered out unnecessary components and standardized so that the data will contain only cyclical patterns and not have the unit effect in the analysis. The research builds up the CLIs from the formative measurement models: Short-Leading Economic Index (SLEI), Financial Cycle (FC), Monetary Condition (MC), and International Transmission by Trade Channel (ITT), whereas the research sets International Transmission by International Monetary Policy Channel (ITM) as a single-item construct. The CLIs are separated into a short-term, medium-term, and long-term leading period. The short-term CLIs include SLEI and ITT, whereas FC is the medium-term CLI, and the long-term CLIs consist of MC and ITM. Regarding results, SLEI and ITT can signal EC at one-quarter ahead, FC leads EC at seven-quarter in advance, and MC and ITM advance signal EC eleven-quarter.

To confirm that EWS by PLS-SEM is outstanding to forecast EC, the research compares the forecasting performance of EWS by PLS-SEM with the CLI by equal weight and the ARIMA model. The evidence is explicit that EWS by PLS-SEM outperforms the benchmark models for all short-term, medium-term, and long-term leading periods.

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Jeerawadee Pumjaroen

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ABBREVIATIONS

Abbreviations	**Equivalence**
ADF	Augmented Dickey-Fuller Unit Root Test
ARIMA	Autoregressive Integrated Moving Average
ASEAN	Association of Southeast Asian Nations
BSI	Business Sentiment Index (next 3 months)
CB-SEM	Covariance-Based Structural Equation Modeling
CLI	Composite Leading Index
EC	Economic Cycle
ECB	European Central Bank
ER	Real Effective Exchange Rate
EWS	Early Warning System
EX	Export Volume Index (exclude Gold)
FC	Financial Cycle
FiveAsia_CLI	OECD CLI for Major Five Asia Countries
GDP	Real Gross Domestic Product
HD	Household Debt
HD_GDP	Household Debt to GDP
HPI	Housing Price Index (townhouse and land)
IMF	International Monetary Fund
IR	Policy Interest Rate
IT	International Transmission
ITM	International Transmission by International Monetary Policy Channel
ITT	International Transmission by Trade Channel
M1	Narrow Money
MC	Monetary Condition
MPI	Manufacturing Production Index
NBER	National Bureau of Economic Research

Abbreviations	Equivalence
OECD	Organisation for Economic Co-operation and Development
OECDplus_CLI	CLI for OECD and non-member economies
OLS approach	Ordinary Least Square
PLS-SEM	Partial Least Squares Structural Equation Modeling
RMSE	Root Mean Square Error
SEM	Structural Equation Modeling
SLEI	Short-Leading Economic Index
USA_CLI	OECD CLI for the United States
VIF	Variance Inflation Factor

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

The world has confronted many economic fluctuations, and many of them ended with the same result: a significant decline in the economy. Some became historic global economic crises. One of the worst economic crises, the Great Depression, occurred in the 1930s. The crisis started in the United States from a bubble in the stock market and then spread over many countries around the world. Another crisis, in 1982, was the Latin Sovereign Debt Crisis, which stemmed from Mexico, Brazil, and Argentina borrowing vast sums of money to develop their countries, especially for infrastructure. This crisis had its origins in the early 1970s when the world economy entered into a recession, interest rates climbed much higher, and currencies of South America depreciated. As a result, these countries could not pay their debt, which led to an economic crisis. The Asian crisis during 1997-1998, also called the "Tom Yum Kung crisis," began in Thailand. During that time, Thailand owed a tremendous amount of debt to foreign entities, which was difficult to pay back. Furthermore, the Thai currency collapsed on July 2, 1997, after the Thai government was forced by mounting international pressure to float its currency, the Baht, freely on the open market. The result was that Thailand could not service its debt. The crisis started in Thailand and spread across the region, with South Korea, Indonesia, Laos, Hong Kong, Malaysia, and other countries around the world also affected. During 2000-2002, the Dot-Com crisis, also known as the Y2K crash, the tech crisis, or the information technology crisis, originated in Western countries during a period of excessive speculation called the Dot-Com bubble. It occurred roughly from 1997 to 2001, a period of extreme growth in the usage and adaptation of the internet. During this period, many internet-based companies, commonly referred to as Dot-coms, were founded. There was excessive speculation in the stock market technology sector, and it peaked on March 10, 2000, when the NASDAQ composite reached 5,133. Soon after, the bubble collapsed during 2000–2002, and many companies completely failed and shut down. The world was hit again by a financial crisis during 2007-2009, also known as the global financial crisis. It is considered the worst crisis since the Great Depression. The crisis began in 2007 from the subprime mortgage market in the USA, which developed into a full-blown international banking crisis with the collapse of the investment bank Lehman Brothers on September 15, 2008. Excessive risk-taking by banks such as Lehman Brothers helped to magnify the financial impact globally. Massive bail-outs of financial institutions and other palliative-monetary and fiscal policies were employed to prevent a possible collapse of the world's financial system. The crisis was nonetheless followed by a global economic downturn, the Great Recession. Recently, the European sovereign debt crisis started in 2010 and continues to the present. It was a multi-year debt crisis that took place in the European Union beginning at the end of 2009. Several Eurozone member states (Greece, Portugal, Ireland, Spain, and Cyprus) were unable to repay or refinance their government debt or to bail out over-indebted banks under their national supervision without the assistance of third parties like other Eurozone countries, the European Central Bank (ECB), or the International Monetary Fund (IMF). This crisis affected a great many countries, regions, and sectors with diminishing wealth effects (Figure 1.1).

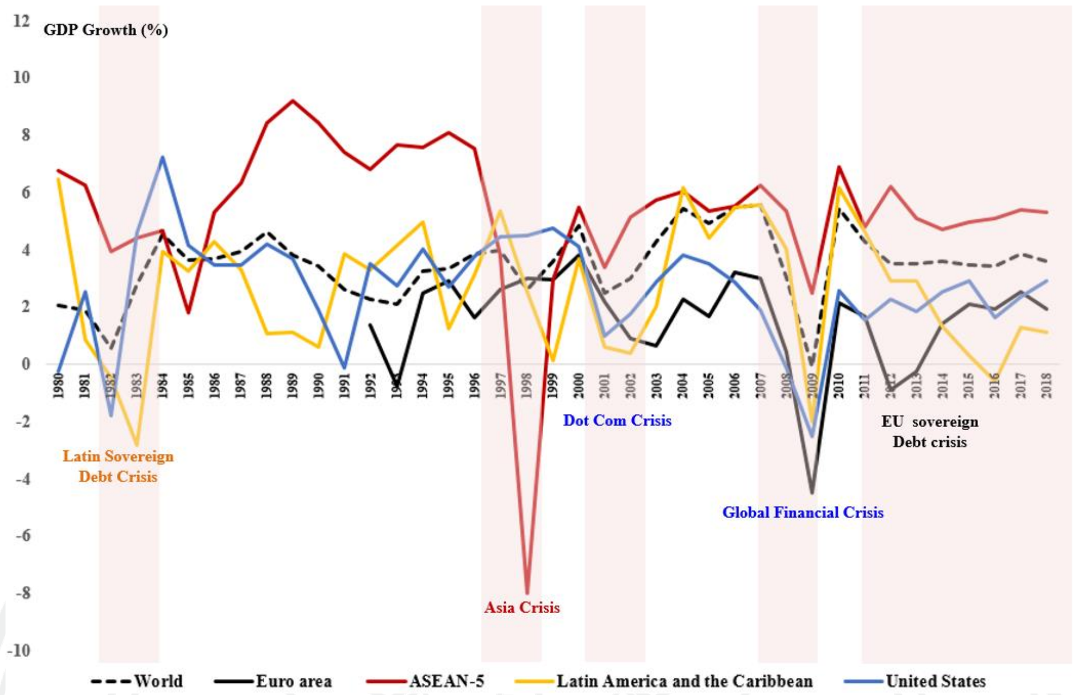


Figure 1.1 The World Economic Fluctuations

Source: Adapted from International Monetary Fund, April 2020

According to Thailand, during 2000-2018, many both domestic and external factors drove fluctuations in the Thai economy. To begin with, the Asian crisis, or Tom Yum Kung crisis, which occurred during 1997-1998, originated in Thailand and propagated to many other countries throughout the world. The event caused the Thai Economy to contract -2.71% and -7.64% in 1997 and 1998, respectively. The impact was especially severe in the second quarter of 1998 when the Real Gross Domestic Product (GDP) of Thailand went down -12.53%. Later, the Dot-Com crisis occurred during 2000-2002 and originated in Western countries. The crisis made the Thai economy sluggish: Thai GDP was 3.44% in 2001. However, it had the most significant impact on the Thai export sector, which contracted -6.58% in 2001, especially in the US market. At that time, the US was a vital Thai export destination, receiving 20.25% of total Thai exports: Thai exports to the US shrank -11.23%. In 2009, the global financial crisis caused the Thai economy to contract again after the Asian crisis. Thai GDP was down -0.68%, and again the Thai export sector was heavily impacted, contracting -14.26%. This global financial crisis was considered the worst crisis since the Great Depression of the 1930s, affecting many countries around the world, and thus causing Thai exports to shrink in almost all markets such as the US, EU, Asia, Africa, Middle East, and South America. The latest crisis to hit the Thai economy was the European sovereign debt crisis, starting in 2010. The crisis has caused the Thai economy to grow at a slow rate. One of the reasons is that Thai exports have been depressed not only in the EU market but also in other markets. Thai exports shrank continuously for three years during 2013-2015.

In addition, the Thai economy has also fluctuated as a result of natural disasters. For example, on December 26, 2004, Thailand was hit by the Indian Ocean tsunami. It caused the Thai GDP to drop to 3.84 in Q1/2005 from 6.64 in Q4/2004. The severe flooding in Thailand that occurred from the end of July 2011 to January 2012 caused the Thai GDP to shrink -4.04 in Q4/2011 (Figure 1.2).

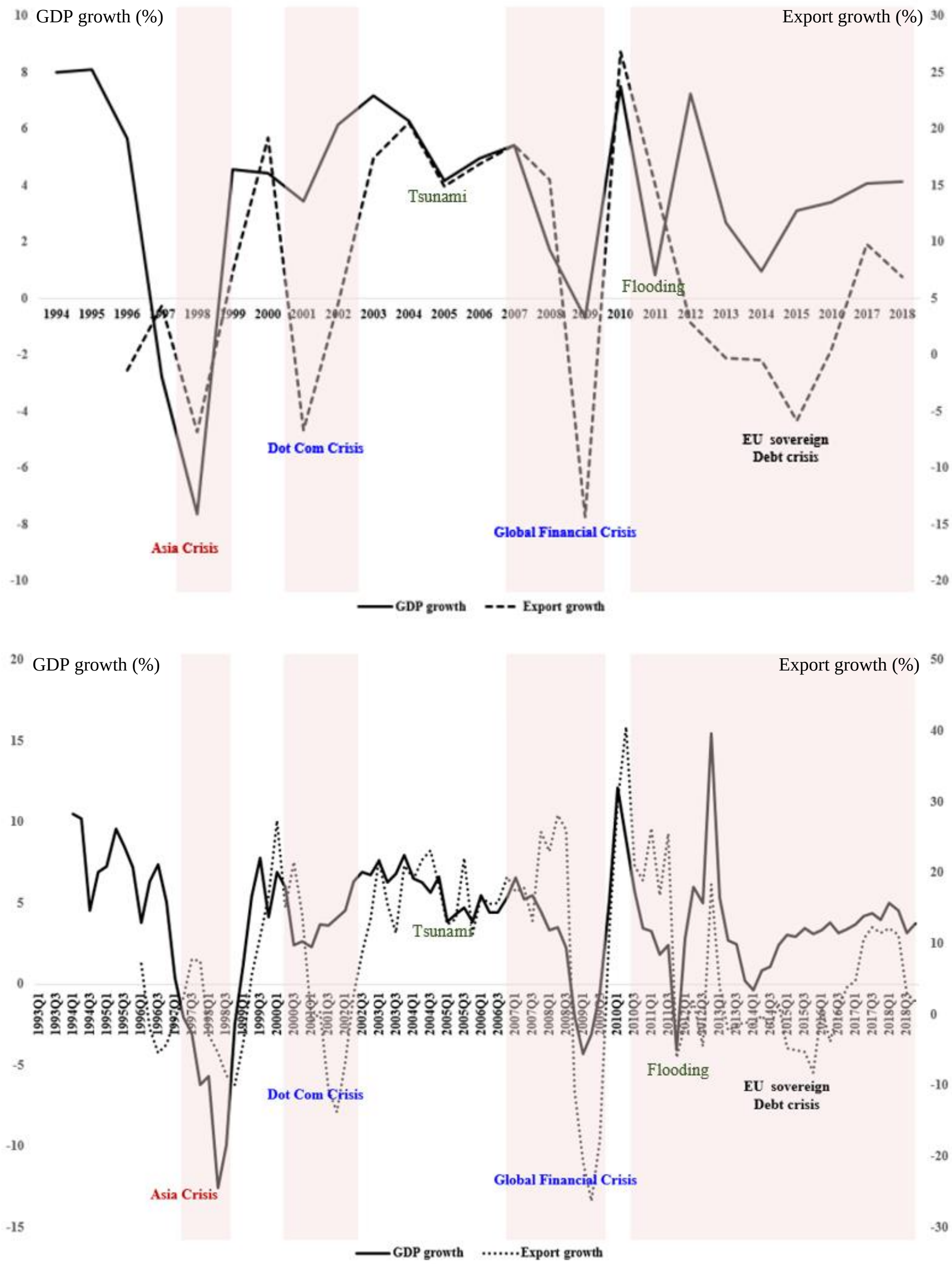


Figure 1.2 Thailand Economic Fluctuations

Source: Adapted from National Economic and Social Development Board (Thailand), 2020; Bank of Thailand, 2020

Due to economic fluctuations, some of which become economic crises, there is interest in developing an Early Warning Systems (EWSs) to signal policymakers before economic damage increases. One of the favorite tools in the EWS area is the leading indicator, which aims to signal ahead economic recessions and recoveries developed by Mitchell and Burns (1938) in the 1930s. However, each leading indicator might have an ability to signal at different periods. As for the Organisation for Economic Co-operation and Development (OECD), it separates leading indicators into two groups: a short-medium (2-8 months) and a longer (over eight months) leading indicator (Gyomai & Guidetti, 2012). Meanwhile, Babecký et al. (2013) classify their economic leading indicators into three groups: a late-warning (1-3 quarters), an early-warning (4-8 quarters), and an ultra-warning (since nine quarters) leading indicator.

Generally, researchers propose using Composite Leading Indexes (CLIs) that are relevant to their leading ability horizons such as short-term, medium-term, and long-term leading indicators in order to improve their predictive power (Levanon, Manini, Ozyildirim, Schaitkin, & Tanchua, 2015; Stock & Watson, 1989). However, they are generally used as early warning tools separately.

To support “Two heads are better than one,” the paper aims to demonstrate that the forecasting ability of the linked CLIs outperforms the individual CLI. Therefore, the study evaluates the relationships of CLIs to forecast the economic cycle (EC) of Thailand during Q1/2003-Q4/2018 by Structural Equation Modeling (SEM). SEM is prevalent to carrying out Covariance-Based Structural Equation Modeling (CB-SEM) analyses. However, there is also another SEM approach, called Partial Least Squares Structural Equation Modeling (PLS-SEM). One of the distinctions between these two methods is the research objective. CB-SEM is suitable for theory testing and confirmation, whereas PLS-SEM is proper for prediction and theory development (Hair, Hult, Ringle, & Sarstedt, 2016; Hair, Risher, Sarstedt, & Ringle, 2019; Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Lowry & Gaskin, 2014; Wold, 1975). The purpose of this research is to construct CLIs and develop an EWS to forecast EC. This research proposes using PLS-SEM to pursue the objectives.

PLS-SEM is prominently appropriate for this task because it can construct CLIs through a measurement model, and evaluate the relationship among those CLIs from a structural model. To forecast EC from the linkages of CLIs by PLS-SEM is brand-new: to my knowledge, no one in the EWS field has applied this method before.

1.2 Research Objectives

1) To identify the Composite Leading Indexes of the economic cycle
2) To develop the Early Warning System to forecast the economic cycle in short-term, medium-term, and long-term periods.

1.3 Scope of the Study

1) The research develops EWS by PLS-SEM using Thailand as the case study.
2) The research studies economic fluctuation from the macroeconomic viewpoint happening from an economic system not related to irregular situations such as natural disasters or political conflict.
3) The EWS is modeled from financial and macroeconomic variables using quarterly data from secondary sources during Q1/2003-Q4/2018.

1.4 Expected Benefits

1) The government and the public sector will have potential CLIs and EWS to forecast EC in the short-term, medium-term, and long-term periods so that they will have sufficient time to prevent or mitigate the effect of economic fluctuation in an appropriate manner.
2) The proposed method in this study could also be applied to forecast other economic indicators such as exchange rate, interest rate, or inflation rate.

1.5 Organization of the Dissertation

To pursue the research objectives, the rest of this research is organized as follows: Chapter 2 provides a literature review of EWS and related concepts, the relationship between economic sectors to forecast EC, and the model used to develop EWS: PLS-SEM. Chapter 3 focuses on the details of the research method used in the research. Chapter 4 presents the results obtained from the data analyses. Finally, Chapter 5 presents conclusions, discussions, and recommendations.

CHAPTER 2

LITERATURE REVIEW

This chapter analyzes the relevant literature to provide the necessary background and terminology as the foundation for the rest of this research. Related concepts and research have been examined to outline the literature framework as the following;

2.1 Early Warning System and Related Concepts
2.2 Relationship between Economic Sectors and their Proxies
2.3 Partial Least Square-Structural Equation Modeling (PLS-SEM)

2.1 Early Warning System and Related Concepts

This section aims to provide the literature about terminologies, methodologies, and related concepts of EWS.

2.1.1 Early Warning System (EWS)

"EWS refers to the class of empirical and theoretical works aimed at the early identification of various costly events, such as imbalances or crashes, in the economy" (Babecký et al., 2011). Owing to several economic crises, researchers were interested in the area of leading indicators and theoretical models explaining such crises. However, it was not until the 1990s that the early warning literature became prevalent because of the currency collapse in some Asian countries, causing to happen the Asian crisis during 1997-1998. The crisis began in Thailand because the Thai government was forced to float the Baht Currency on the open market, causing the Baht to depreciate dramatically. At that time, Thailand owed a massive amount of debt to foreign entities. As a result, the country could not service the debt, sparking an economic crisis across the region and slowing the world economy. This crisis caught the interest of Kaminsky, Lizondo, and Reinhart (1998), who suggest that it should be the symptoms signaling the crisis in advance, and those signals should allow the policymakers to prevent or mitigate the crisis. Therefore, they proposed an early warning system methodology for currency crises: the signals approach.

There are various methodologies used to develop EWS. Most of them are constructed from potential leading indicators to give the prediction of the economic crisis. The popular approaches are as follows.

1) **The Signals Approach:** The Signals Approach was proposed by Kaminsky et al. (1998).The method compares the value of the variable between crisis and non-crisis periods to set a threshold separately for each indicator. Instead of monitoring individual potential leading indicators, some studies combine those selected leading indicators into an index and set a threshold for the corresponding indicators simultaneously. Regarding this method, EWS will signal if the selected leading indicator (or composite index) is above a certain threshold. The threshold can be identified by minimizing the Noise-to-Signal Ratio, as explained below.

Table 2.1 The Performance of an Indicator

	Crisis	No Crisis
Signal issued	A	B
No signal issued	C	D

$$\text{Good signals} = \frac{A}{A+C}$$

$$\text{Bad signals} = \frac{B}{B+D}$$

$$\text{Noise-to-Signal Ratio} = \frac{B/(B+D)}{A/(A+C)}$$

Where

A is the number of times of which the indicator signals, and a crisis occurs.

B is the number of times of which the indicator signal, but no crisis occurs.

C is the number of times of which the indicator does not signal, but the crisis occurs.

D is the number of times of which the indicator does not signal, and no crisis occurs.

2) **Regression Model for Discrete Dependent Variable:** The discrete regression is applied to estimate the probability of crises of which the dependent variable represented the event of crises: yes or no. EWS will alarm when the probability reaches a certain threshold. Initially, the researcher applies binary logit or probit models for this task (Pattillo & Berg, 1998). Subsequently, they have been replaced with multinomial models (Bussiere & Fratzscher, 2006), which extend the discrete choice from two (yes or no) to more states, such as crisis, post-crisis, and tranquil periods. Recently, there is a dynamic panel logit (Babecký et al., 2011) applied for EWS.

3) **Composite Leading Index:** A Composite Leading Index (CLI) aims to provide an advanced signal for recessions and recoveries of the business cycle. It aggregates leading indicators to display a reasonably consistent leading relationship with the reference series. Several studies use CLI as the EWS for EC. For example, Gyomai and Guidetti (2012) apply CLI for both individual countries and the country zone. Bank of Thailand (n.d.) also uses the CLI as a tool for monitoring and warning the Thai economy.

2.1.2 Business Cycle

Business cycles were pioneered by Burns and Mitchell (1946), which are fluctuations of the whole economic activity. A cycle is identified by the co-movement of many economic activities in the same duration, which fluctuate recurrently expansions and contractions. The length of the business cycle is over one year. There are different concepts of the business cycle. Start with the classical cycle or trend cycle is the fluctuation of the level of economic activities (Burns & Mitchell, 1946). Next is the growth cycle, which is defined as the movement in economic activities as they deviate up and down from the long-run potential level or fluctuations in the output-gap (Mintz, 1969). Finally, the growth rate cycle refers to the deviation of the growth rate of economic activities (Layton & Moore, 1989).

2.1.3 **Leading Indicator**

Leading indicators are developed to predict the stages of the economy. Working for The National Bureau of Economic Research (NBER), Mitchell and Burns (1938) identified various business indicators for the United States, categorizing them into a set of leading, coincident, and lagging indicators, which refer to their indicating ability before, during or after the economic activity.

1) **Identification of Leading Indicators:** Regarding Babecký et al. (2011), leading indicators can be identified by three approaches. 1) A theory-based study is an approach to identify potential leading indicators from the theoretical papers survey. It usually works with a relatively narrow set of potential indicators, but sometimes this set is enlarged to include various transformations of the same data series (Kaminsky et al., 1998; Kaminsky & Reinhart, 1999). The risk of this approach is that the theory-based studies are limited in their search for indicators by a lack of theoretical models that can comprehensively capture the reasons for various types of crises and imbalances. 2) A systematic literature review is an approach that researchers scrutinize previously published research for useful leading indicators and create extensive data sets by including all detected indicators, and sometimes also various transformations (Frankel & Saravelos, 2010; Rose & Spiegel, 2009). However, there is a risk to the method; systematic literature reviews inherit various omissions from the surveyed research unless they add indicators of their own. 3) All variables in the database, this approach will take all variables in a selected database and add various transformations. Nevertheless, studies relying on one database may miss indicators available elsewhere.

   According to Babecký et al. (2011), they follow the second approach, which is the systematic literature survey. However, they reduce the risk of missing critical potential indicators in their analysis by adding some potential leading indicators based on their judgment.

Nonetheless, there might be such a large number of leading indicator candidates such that in practice, it is not convenient for researchers and policymakers to monitor all of them. Therefore, the researchers generally select the potential leading indicators from leading indicator candidates. Many of them start with the literature review for identifying leading indicators. Then they usually test them by using econometric or statistical models, such as Bayesian model averaging (Babecký et al., 2011), Partial least square path modeling (Serrano-Cinca, Fuertes-Callén, Gutiérrez-Nieto, & Cuellar-Fernández, 2014) and Turning points of business cycles and Conditional probability (Zhuang, Edwards, & Capulong, 2001).

2) **Leading Period:** The leading period is the time duration that leading indicators can give a signal before a crisis happens. Babecký et al. (2011) use Panel vector autoregression, and Gyomai and Guidetti (2012) apply a turning point approach for identifying the leading period. However, each leading indicator could have a different leading period.

Gyomai and Guidetti (2012) categorize leading indicators into two groups: a short-medium (2-8 months) and a longer (over eight months) leading period. Babecký et al. (2013) categorize them into three groups: a late-warning (1-3 quarters), an early-warning (4-8 quarters), and an ultra-warning (al least nine quarters) leading period.

2.1.4 **Composite Leading Index**

Stock and Watson (1989), whose work is based on the study of Mitchell and Burns (1938), found that the combining of indicators into a composite index has more predictive power of economic activities than an individual one because it aggregates multiple sources of economic fluctuation. Meanwhile, Levanon et al. (2015) also support that CLIs have the ability over individual leading indicators. Hence, researchers generally combine leading indicators as CLIs, which are relevant to their leading ability horizons such as short-term, medium-term, and long-term CLI. The

Organisation for Economic Co-operation and Development (OECD) has developed CLIs for OECD member countries for early signaling the turning points of economic activities. Applying the concept of growth cycle from Mintz (1969), OECD CLIs aim to predict a reference cycle, which is a proxy for economic activities fluctuating to its long term potential (Gyomai & Guidetti, 2012; OECD, 1987). OECD CLIs are constructed from the potential leading indicators with equal-weight. Nowadays, there are CLIs both for OECD members and non-member countries almost around the world.

2.2 Relationship between Economic Sectors and their Proxies

This section contains literature regarding the relationship between the monetary sector, the financial sector, the real sector, and the global sector, as well as the indicators to measure those economic sectors.

2.2.1 Relationship between Economic Sectors

Previous literature supports that there is a relationship between the economic sectors, such as the monetary sector, the financial sector, and the global sector to the real economic sector. Moreover, those can signal the economic fluctuation at different horizons.

To begin with, monetary policy, which is generally managed by the central bank. The ultimate goal of monetary policy is to support the national economic expansion in the long run. The essential objective of monetary policy is to stabilize the financial sector because financial stability plays a crucial role in harnessing economic growth with sustainability, (Warapong Wongwachara, Bovonvich Jindarak, Nuwat Nookhwun, Sophon Tunyavetchakit, & Chutipha Klungjaturavet, 2018). Generally, financial instability is captured by the Financial Cycle (FC) fluctuating from peak to trough continuously. The peaks of the financial cycle tend to be followed by financial crises and economic fluctuations (Borio, 2014; Borio, Drehmann, & Xia, 2018). There is a trade-off relationship between FC and the real economy; the increase of FC (the financial imbalance) tends to be followed by real economic downturn (Warapong Wongwachara et al., 2018). Furthermore, the domestic economy may be affected by global economic fluctuations through international transmission (Ericsson, Jansen, Kerbeshian, & Nymoen, 1998; Schmitt–Grohé, 1998) by both the trade channel and International monetary policy channel (Hickman, 1974; Sethapramote, 2015). Besides, in the short-term, policymakers usually monitor a group of indicators capturing the fluctuations of EC in advance, called a short leading economic index (SLEI). The SLEI provides early signals of EC, which generally can lead EC 1-3 quarters (Babecký et al., 2013; Bank of Thailand, n.d.; Gyomai & Guidetti, 2012).

2.2.2 **Proxies of the Economic Sectors**

The economic sectors cannot be directly observed; therefore, the study reviews the reasonable indicators to represent them or to be their proxies, which are constructs (also called latent variables or unobserved variables).

1) **Economic Cycle (EC):** The economic cycle is fluctuations in economic activities, which shows the increase and decrease in the production of goods and services in the economy. Generally, the cycle of Real Gross Domestic Product (GDP) or Manufacturing Production Index (MPI) is applied to identify EC or the proxy of the economic activities (Bilan, Gavurova, Stanisław, & Tkacova, 2017).

2) **Short-Leading Economic Index (SLEI):** SLEI is a combination of short-term leading indicators aiming to notice the fluctuations of EC in advance 1-3 quarters (Babecký et al., 2013; Bank of Thailand, n.d.; Gyomai & Guidetti, 2012). Bank of Thailand constructs SLEI to give an advance signal of the Thai economy in the short-term: ahead 3-4 months. It includes seven components: Business Sentiment Index (next three months) (BSI), Export Volume Index (excluding gold), Money Supply, Authorized Capital of Newly Registered Companies, New Construction Permits, Stock Exchange Index of Thailand, and Dubai Oil Price Index.

3) **Financial Cycle (FC):** Regarding the definition of FC, there is no consensus; nonetheless, it usually aims to capture financial instability (Grinderslev, Kramp, Kronborg, & Pedersen, 2017) and forecast financial crises (Warapong Wongwachara et al., 2018). In general, FC mainly consists of credit and property prices (Alternatively, it can include other less essential components), which aim to represent the interaction between the financing constraints (credit) and the perceptions of value and risks (property prices) (Borio, 2014; Borio et al., 2018; Drehmann, Borio, & Tsatsaronis, 2012; Grinderslev et al., 2017). Focusing on the medium-term of the financial cycle, Borio et al. (2018); Drehmann et al. (2012) construct FC using three components: Credit, Credit-to-GDP ratio, and Property Prices. Following the concept of Drehmann et al. (2012), Warapong Wongwachara et al. (2018) construct FC of Thailand with equal weight from four components: Credit Aggregates, Credit-to-GDP Ratio, the Single-Detached House (including land) Price Index, and Land Price Index.

4) **Monetary Condition (MC):** The Bank of Canada initially developed MC as the country's operational targets by combining Interest Rate and Exchange Rate (Freedman, 1996). It has gained widespread use; various organizations within both government and private sectors construct MC to assess the stance of Monetary Policy (Ericsson et al., 1998). Memon and Jabeen (2018) also created MC for Gulf countries and interpret the changes of the index as the tightening (MC increasing) or loosing (MC decreasing) of monetary conditions; moreover, they also conclude that MC has the ability to forecast GDP.

5) **International Transmission (IT):** IT refers to the economic fluctuation in one or a group of countries affecting other countries. So they are interdependent, displaying economic correlation across countries (Cantor & Mark, 1988), and broad literature concludes that they positively correlate (Schmitt–Grohé, 1998). The increase of trade and financial

integration has resulted in countries having more synchronization in the business cycle (Kose, Prasad, & Terrones, 2003). The main channel of IT as the following:

- **International Transmission by Trade Channel (ITT):** Sethapramote (2015) studies the business cycle synchronization of the Association of Southeast Asian Nations (ASEAN) from the internal and external regions. His study points out that trade transmission is an essential factor in ASEAN synchronization because they rely on export revenue. Therefore, the economic fluctuation of their major partner countries of exportation can affect them.
- **International Transmission by International Monetary Policy Channel (ITM):** The fluctuation of the global economy likely transmits to the domestic economy via international monetary policy. The variation in the global money supply, which relies on the global economy, tends to affect the national interest rate and currency (Hickman, 1974).

2.3 Partial Least Square Structural Equation Model (PLS-SEM)

Structural Equation Model (SEM) can be categorized into two types: Covariance-Based (CB-SEM) and Variance-Base Structural Equation Modeling (VB-SEM) or Partial Least Square Structural Equation Modeling (PLS-SEM). These two approaches have a distinction.

CB-SEM involves a Maximum Likelihood procedure with the objective of theory confirmation. It aims to minimize the difference between the estimated and the observed covariance matrices to evaluate model parameters, and the data applied in the model have to be a normal distribution and quite a big sample size, whereas PLS-SEM relies on an Ordinary Least Square (OLS) approach whose purpose is to forecast the target constructs. It attempts to maximize the explained variance of the endogenous constructs. The method can estimate a complex model with all data distribution and a small sample size. Therefore, there is much literature applying PLS-SEM with a forecasting purpose using a small sample size (Castro-González & Leon, 2017; Jabeur & Sghaier, 2018). Because of its outstanding ability, PLS-SEM has become a common statistical method in many fields of science (Hair et al., 2016; Hair et al., 2014).

The prediction is the ultimate goal of the research, and also data available for the analysis is quite limited in terms of sample size. Moreover, the model is composed of a single-item construct, and the entire construct relies on the formative concept; therefore, PLS-SEM is the most suitable for the study (Hair et al., 2016; Lowry & Gaskin, 2014).

PLS-SEM was developed by Wold (1975) and extended later by Lohmoller (1989), Bentler and Huang (2014), Dijkstra (2014), and Dijkstra and Henseler (2015) as cited in Hair et al. (2016). The approach combines the principal components analysis and the OLS regressions to estimate partial model structures. The method is composed of two parts: a measurement model and a structural model. The measurement model is to establish a construct (also called a latent variable or an unobserved variable) from their indicators with unequal weight, and the structural model evaluates the relationships among those constructs. The PLS-SEM algorithm estimates parameters in the model to maximize the explained variance of dependent variables or called endogenous variables in PLS-SEM.

2.3.1 Data Characteristic of PLS-SEM

1) **Sample size:** PLS-SEM can perform well with a small sample size (Chin, 1999; Hui & Wold, 1982; Reinartz, Haenlein, & Henseler, 2009) when many constructs and various indicators are included in a model (Fornell & Bookstein, 1982; Willaby, Costa, Burns, MacCann, & Roberts, 2015). It is possible because PLS-SEM does not estimate the whole relationship at one time; on the other hand, it applies partial regression relationships to separately estimate measurement and structural models by OLS regressions. Even though PLS-SEM could work well with a small sample size, it should meet the minimum requirement of 10 times rule. The sample size should be at least ten times the largest number of indicators building

up a construct in a formative measurement model, or it should be at least ten times the largest number of paths pointing at a particular construct in the structural model (Barclay, Higgins, & Thompson, 1995).

2) **Data Distribution:** PLS-SEM estimates a robust model when performing data, both normal distribution and nonnormal distribution with skewness or kurtosis properties (Reinartz et al., 2009). Nonetheless, the problem of collinearity, heteroscedasticity, and influential outliers still affects the parameter estimation in PLS-SEM when using OLS regressions.

3) **Data Scale:** PLS-SEM is suitable for the continuous variables that are ratio or interval scale. However, it could perform a categorical variable: an ordinary scale or a nominal scale. According to a nominal scale, it should not apply as the ultimate endogenous variable; instead, it might work as the moderators in the PLS-SEM (Hair, Sarstedt, Ringle, et., 2012 as cited in Hair et al., 2016)

4) **The Number of Indicators per Construct:** The number of indicators to form the constructs can be both a single-item measure and multiple-item measures. The single-item is suitable to measure observable characteristics such as sales, quotas, profits (Hair et al., 2016). If not the case of measuring observable characteristics, the use of single-item should consider the guidelines of Diamantopoulos, Sarstedt, Fuchs, Wilczynski, and Kaiser (2012): the single-item should be used only under the following situation.
   - Small sample size: Available data is a small sample size.
   - Weak effects: Path coefficient is 0.30 or lower.
   - Items highly homogeneous: The original multi-item scale expresses highly homogeneous such as Cronbach's alpha > 0.90.
   - Semantical redundant Item: The items are semantically redundant.

2.3.2 Variable Types in PLS-SEM

The variables in PLS-SEM consist of two types: constructs and indicators.

1) **Constructs:** The constructs (also called an unobserved variable or a latent variable) are variables that cannot be directly measured. There are two types of constructs: exogenous and endogenous constructs. The exogenous constructs are variables that explain other constructs in the model. In other words, the exogenous constructs are independent unobserved variables in a structural model. While the endogenous constructs act as dependent unobserved variables by that the exogenous constructs in the model explain.

2) **Indicators:** Indicators are variables that are directly-measured, which aim to ground their constructs.

2.3.3 Model Characteristic in PLS-SEM

Partial least square-structural equation modeling (PLS-SEM) includes two types of models: a measurement and a structural model, as in Figure 2.1

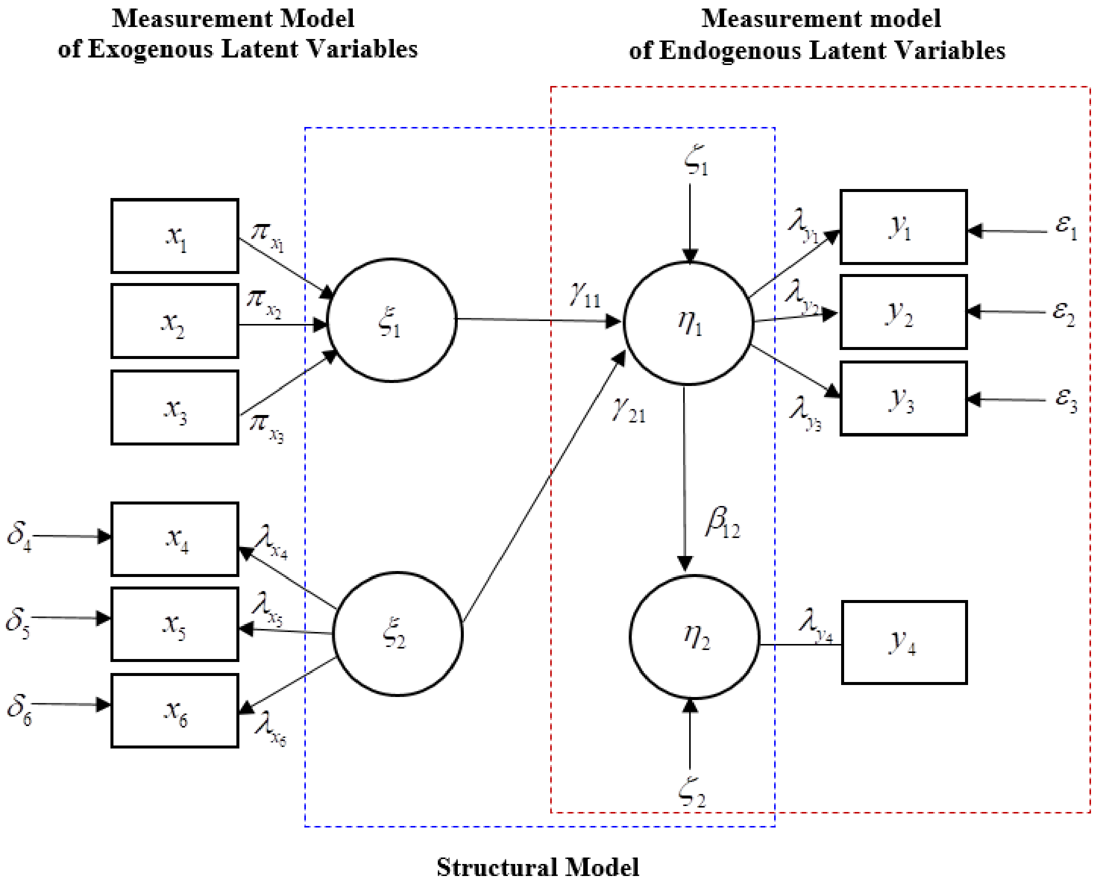


Figure 2.1 A Simple Partial Least Square Structural Equation Model

Where

ξ represents an exogenous construct.

η represents an endogenous construct.

x represents an indicator of an exogenous construct.

y represents an indicator of an endogenous construct.

γ represents a structural coefficient relating to an exogenous construct and an endogenous construct.

B represents a structural coefficient relating between endogenous constructs.

π_x represents a weight of an indicator in a formative exogenous construct.

π_y represents a weight of an indicator in a formative endogenous construct.

λ_x represents a loading of an indicator in a reflective exogenous construct.

λ_y represents a loading of an indicator in a reflective endogenous construct.

δ represents an error of indicator in a reflective exogenous construct.

ε represents an error of indicator in a reflective endogenous construct.

ζ represents a residual of an endogenous construct.

2.3.3.1 Measurement Model

The measurement model (also called the outer model) displays the relationships between the construct and its indicators. Since the construct cannot be directly measured, PLS-SEM builds it up from the indicators by a measurement model. There are two types of measurement models: a reflective and a formative measurement model as in Figure 2.2.

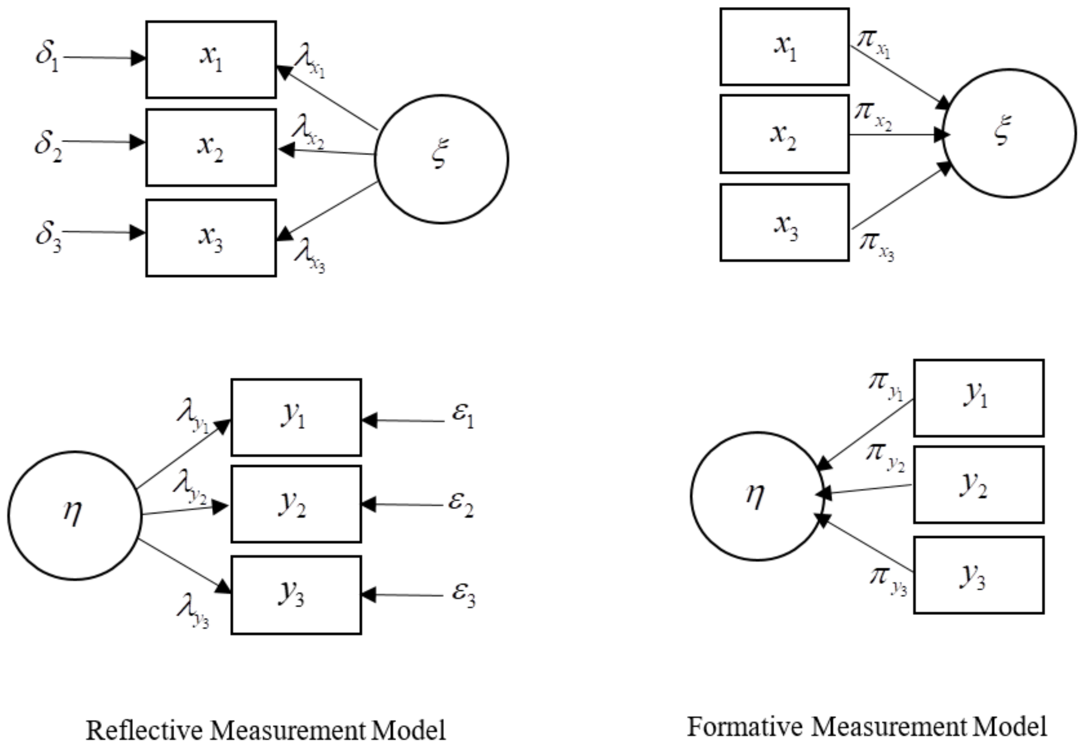


Figure 2.2 Reflective and Formative Measured Model

1) **Reflective Measurement Model:** A reflective measurement model refers to the model in which the changing of a construct affects the changing of its indicators. Since all indicators in the same reflective model are affected by the same domain (the same

construct), those indicators in the same reflective model should highly correlate with each other. Hence, the reflective measurement approach focuses on maximizing the overlap between interchangeable indicators. This relationship can be explained by the arrows pointing out of the construct to the reflective indicators. The coefficient of the reflective relation is called loading. The relationship in the reflective measurement model shows the following.

$$X = \Lambda_x \xi + \delta$$
$$Y = \Lambda_y \eta + \varepsilon$$

Where

ξ represents a vector of the reflective exogenous constructs.

η represents a vector of the reflective endogenous constructs.

X represents a vector of the indicators in a reflective exogenous construct.

Y represents a vector of the indicators in a reflective endogenous construct.

Λ_x represents a matrix of the loadings in reflective exogenous constructs.

Λ_y represents a matrix of the loadings in reflective endogenous constructs.

δ represents an error vector of the indicators in reflective exogenous constructs.

ε represents an error vector of the indicators in reflective endogenous constructs.

2) **Formative Measurement Model:** There are two types of formative measurement models in the structural equation modeling (SEM): a causal and a composite index. The causal index is based on the concept that the indicators cause to happen the construct; in other words, the causal indicators cause the change of the construct. Therefore the causal index will have an error term, which represents the other causes of the construct not included in the model. The composite index intends to form the unobserved variable by the linear combination completely. It acts

as a proxy of an unobserved concept. Hence, the formative construct of the composite concept will not have the error term. However, the PLS-SEM only depends on the composite index concept (Diamantopoulos, 2006, 2011 as cited in Hair et al., 2016).

The formative construct may stem from various content domains so that the approach generally minimizes the overlap between complementary indicators. Regarding the formative Relationship, it can be explained by the arrows from the formative indicators pointing into the construct and the relationship between indicators and the construct called the weights. The relationship in the formative measurement model is the following.

$$\xi = \Pi_x X$$

$$\eta = \Pi_y Y$$

Where

ξ represents a vector of the formative exogenous constructs.

η represents a vector of the formative endogenous constructs.

Π_x represents a matrix of the weights in formative exogenous constructs.

Π_y represents a matrix of the weights of formative endogenous constructs.

X represents a vector of the indicators in a formative exogenous construct.

Y represents a vector of the indicators in a formative endogenous construct.

2.3.3.2 Structural Model

A structural model (also called the inner models) aims to explain the relationships between the constructs. There are two main issues of concern when constructing the structural model: the sequence of constructs and the relationship between those constructs because they represent the hypotheses and their Relationship to the theory being tested. These issues should be based on the theory, logic, or practical experience of the researchers.

1) **The Sequence of Constructs:** The sequence of constructs will be displayed from left to right in general. The left constructs act as independent variables, which are assumed to precede and predict the constructs on the right acting as dependent variables. The constructs that perform only as independent variables are referred to as exogenous constructs, which generally will be on the left of the structural model. They have only an arrow pointing out of them (no arrow pointing into them). While the dependent variables that have the arrow pointing into them are referred to as endogenous constructs, which generally will be in the middle or on the right of the structural model. Generally, the endogenous constructs in the middle of the structural model will perform as both independent and dependent variables in the model, which have both arrows pointing out of them and arrows pointing into them. The endogenous constructs on the right of the model only have arrows pointing into them, and they only act as the dependent variable called target or final endogenous constructs.

2) **The Relationship between Constructs:** The relationship between constructs is normally displayed by arrows pointing from the left to the right of the structure model. The constructs on the left of the model predict the constructs on the right side. If the relationships have the structural theory to support, it will be referred to as a causal link. Nevertheless, it will be the trade-off between theoretical soundness (including more relationships to support the theory) and model parsimony (using fewer relationships). The parsimonious model should be of more concern, according to Falk and Miller (1992, P. 24). They say that "a parsimonious approach to the theoretical specification is far more powerful than the broad application of a shotgun meaning." The structural model has a relationship as the following.

$$\eta = \mathrm{B}\eta + \Gamma\xi + \varsigma$$

Where

B represents a matrix of the structural coefficients relating to endogenous variables.

Γ represents a matrix of the structural coefficients relating to exogenous and endogenous variables.

ζ represents a vector of the residual terms.

2.3.4 PLS-SEM Evaluation

The evaluation of the PLS-SEM results is separated into two paths relating to the type of model: measurement and structural model. Some of those evaluations are related to parameter significance testing; however, PLS-SEM lacks a normality assumption so that it relies on a nonparametric bootstrap procedure.

The bootstrap procedure is the method to test parameter significance in PLS-SEM, such as weights, loadings, and path coefficients. The bootstrapping is a method to create more samples from the original data by randomly sampling the observed population from the original sample population with replacement (Efron & Tibshirani, 1986). The coefficients estimated from bootstrapping will be assumed as an approximate sampling distribution, and its standard deviation is viewed as the parameter's standard error (Henseler, Ringle, & Sinkovics, 2009).

For parameter testing of the hypothesis whether the parameter is zero in the population ($H_o : w = 0,\ H_1 : w \neq 0$), a student's t-test is taken to test the hypothesis according to the following formula:

$$t = \frac{w}{se(w)}$$

Where

t represents t-value.

w represents the parameter value estimated from the original data set.

$se(w)$ represents standard error of the parameter w from bootstrapping procedure.

2.3.4.1 Measurement Model Evaluation

Evaluation of a measurement model is to assess the reliability and validity of the construct. Using several indicators to measure one concept represented by the unobserved variable or construct is the main idea to improve accuracy because it is based on the assumption that those indicators could represent different aspects of the construct's concept. However, using more indicators to measure one concept still tends to contain some level of measurement error, both random and systematic error, which affect the reliability and validity of the measurement model. The evaluation of measurement models differs from their concept: a reflective or formative concept. This section will explain the evaluation of the reflective measurement model in brief and describe the evaluation of the formative measurement model in detail because there is no reflective measurement model in the conceptual model.

1) **Reflective Measurement Models Evaluation:** Evaluation of the quality of reflective measurement models is based on an internal consistency perspective. The goal is to be confident that the construct measures are reliable and valid. Therefore, the research should consider indicator reliability, internal consistency-reliability, convergent validity, and discriminant validity.

2) **Formative Measurement Models Evaluation:** Evaluation of the quality of formative measurement models aims to ensure that a formative measurement can capture the domain of the considerable construct. Therefore, the research should evaluate the model by considering content validity, convergent validity, indicator collinearity, and statistical significance and relevance of the formative indicators as suggested by Hair et al. (2016); Hair et al. (2019); Hair et al. (2014).
   - **Content Validity:** To ensure that formative indicators can capture all facets of the domain construct, expert adjustment and literature review help establish content

validity. (Diamantopoulos & Winklhofer, 2001; Jarvis, MacKenzie, & Podsakoff, 2003 as cited in Hair et al., 2016).

- **Convergent Validity:** Redundancy analysis is applied to measure the convergent validity by assessing the correlation of the formative construct with an alternative measure of the same concept. This method was initially proposed by Chin (1998) to tests whether the formative measure highly correlates to an alternative reflective measure of the same construct. Later, Cheah, Sarstedt, Ringle, Ramayah, and Ting (2018); Sarstedt, Wilczynski, and Melewar (2013) proposed to use an alternative-single item that can capture the core concept of the considering formative construct: sufficiency, to be an alternative measure. The conclusion of convergent validity exhibits when the absolute correlation of formative construct and the alternative is at least 0.70 or the coefficient of determination is 0.50 or higher.
- **Indicator Collinearity:** The formative indicators in the same construct should not be interchangeable, which is different from a reflective measurement model. In other words, they should not have a high correlation between each other in the same construct because it will lead to the collinearity problem, which causes a spurious relationship between indicators and formative construct: incorrect weight estimation. Variance Inflation Factor (VIF) is frequently used to evaluate the collinearity problem. It is the statistical value to verify whether the collinearity problem exhibits among leading indicators in the same construct. The conclusion of no collinearity problem exhibits when VIF is less than 5 (Hair et al., 2016; Hair et al., 2019).

$$VIF_{x_i} = \frac{1}{1-R_{xi}^2} = \frac{1}{TOL_{x_i}}$$

Where

VIF_{x_i} represents the variance inflation factor of x_i.

x_i represents the indicator i in the considering formative construct.

$R_{x_i}^2$ represents the amount of x_i's variance associated with the other indicators in the same formative construct.

TOL_{x_i} represents the tolerance that is the amount of variance of indicator x_i not explained by the other indicators in the same formative construct.

- **Statistical Significance and Relevance of the Formative Indicators:** In considering the retaining or removing of the indicators of a formative measurement model, first of all, the research assesses the weight significance from the bootstrapping. The weight stems from multiple regression between the construct and their indicators, which imply as dependent and independent variables, respectively. It is considered as the relative importance of the indicator to their construct. The research will keep considering indicators if their weights are significant (considering as relative contribution). However, the statistical significance of weights gets affected by the number of formative indicators in the same construct. The more indicators included in the construct, the more nonsignificant weights will become (Cenfetelli & Bassellier, 2009). Assuming the number of uncorrelated indicators in the construct, the maximum weight is related to the number of formative indicators (n) in the construct: $1/\sqrt{n}$ (Hair et al., 2016).

However, if an indicator's weight is not significant but its loading is high (≥ 0.50), or significance with the strong theory support (considering as absolute contribution), it also will be retained in the construct. Loading in the formative construct is the product of simple regression between the construct (dependent variable) and each indicator (independent variable), which is considered as the absolute importance of the indicator to their construct. Otherwise, the indicator should be removed from the model.

Considering the indicator relevance, the value of standardizing indicator weights generally are between -1 and 1. However, if they are out of this range, it might be because of the collinearity problem or small sample sizes.

2.3.4.2 Structural Model Evaluation

The evaluation of the structural model aims to assess the model's ability to predict the endogenous constructs and the significance of the relationship between constructs. Assessment of the structural model should consider the collinearity between constructs, the statistical significance and relevance of the path coefficients, the coefficient of determination (R^2), and the effect size (f^2).

1) **Collinearity Assessment:** Based on the regression procedure, assessing the collinearity issue is to confirm that there is no spurious relationship in the structural model between constructs. The similarity to a formative measurement model, VIF, is the value to assess the collinearity problem. A serious collinearity problem will occur if VIF values are above 5.0 (Hair et al., 2016; Hair et al., 2019; Hair et al., 2014).

2) **Statistical Significance and Relevance of the Path Coefficients:** Path coefficients represent the relationship between constructs in a structural model, which is based on the theoretical hypotheses. The coefficient values of standardized path coefficients generally are between -1 to 1 (in some cases, they might be out of this range). Bootstrapping is taken to estimate a standard error to explore the path significances of both direct and indirect relationships between the constructs. The research also considers the relevance of the path coefficients in terms of size and sign relevance to the literature review (Hair et al., 2016; Hair et al., 2019; Hair et al., 2014)**.**

3) **Coefficient of Determination (R^2):** Predictive accuracy is a central goal of PLS-SEM: R^2 is the statistical value commonly used to assess the predictive power of the structural model. R^2 represents the variance explained of the considerable endogenous construct by all other exogenous constructs related to it, which is referred to as in-sample predictive accuracy. The range of R^2 is between 0 and 1, while the higher value means a greater power of prediction. According to Hair et al. (2016); Hair et al. (2019); Hair et al. (2014), if R^2 of an endogenous construct is equal to or greater than 0.25, 0.50, or 0.75, it will be considered as weak, moderate or substantial predictive power, respectively. Nevertheless, based on the context, in some cases, a very low value of 0.10 for R^2 is satisfactory (Hair et al., 2019).

In some cases, the complex model with too high R^2 is overfitted the data because the model fits the random noise in the sample rather than reflects the population. Therefore, that model might fit only its sample and not fit on other samples drawn from the same population (Sharma, Sarstedt, Shmueli, Kim, & Thiele, 2019). Hence, the research should consider the model with both high R^2 and fewer paths pointing to the target construct: parsimonious model.

4) **Effect Size (f^2):** Assessing f^2 is the addition of evaluating R^2. f^2 evaluates whether the omission of the specific predictor construct will make a substantive impact on the endogenous construct. If f^2 value is over 0.02, 0.15, and 0.35, it will be considered as a small, medium, and large effect, respectively (Cohen, 1988 as cited in Hair et al., 2016; Hair et al., 2019). Typically, when considering the size of the path coefficients and f^2, they will provide the same rank order of the predictor constructs' relevance in explaining a dependent construct in the structural model. If they provide a different rank, the effect size (f^2) should be reported by request to explain the presence of, for example, partial or full mediation (Nitzl et al., 2016 as cited in Hair et al., 2019).

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

Where

f^2 represents Effect size.

$R^2_{included}$ represents R^2 of the endogenous construct from a full model including the specific predictor construct.

$R^2_{excluded}$ represents R^2 of the endogenous construct from a reduced model excluding the specific predictor construct.

CHAPTER 3

RESEARCH METHOD

The chapter focuses on the methodology to develop the Early Warning System (EWS) for the economic fluctuations of Thailand. The empirical study utilizes time series data based on the literature review to construct Composite Leading Indexes (CLIs). Subsequently, it analyzes the relationship among them to forecast the Economic Cycle (EC) by Partial Least Square Structural Equation Modeling (PLS-SEM). The methodology can be summarized as follows:

3.1 Research Methodology Framework
3.2 Reference Variable and Composite Leading Indexes of EC
3.3 Conceptual Framework and Hypotheses
3.4 Data and Data sources
3.5 Data Preparation
3.6 EWS by PLS-SEM
3.7 Evaluation of EWS's Forecasting Performance

3.1 Research Methodology Framework

The research aims to identify CLIs and develop EWS to forecast EC in short-term, medium-term, and long-term periods. To pursue the purposes, first, the research reviews the literature regarding the CLIs that tend to lead EC and also the relationship between them to ground the conceptual model. Then time series data regarding the literature are collected and prepared for the analysis. Consequently, the research estimates the relationship of those CLIs to forecast EC by PLS-SEM. Finally, to ensure that the EWS by PLS-SEM is outstanding for forecasting EC, the analysis compares the forecasting performance between EWS by PLS-SEM and the benchmark models**.** The following is the methodology framework.

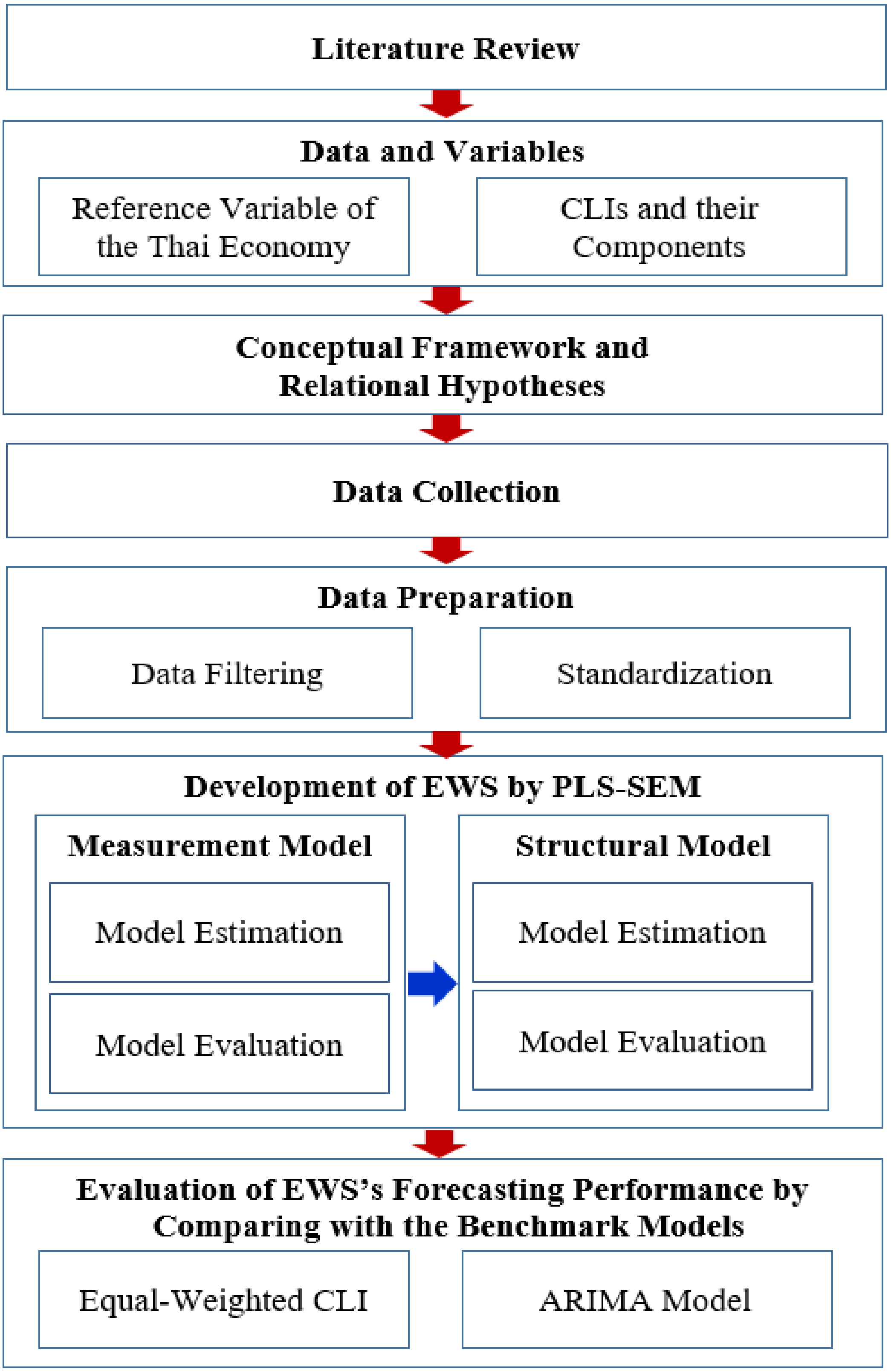


Figure 3.1 Research Methodology Framework

3.2 Reference Variable and Composite Leading Indexes of EC

The research identifies the reference indicator and CLIs of the Thai economy based on the literature review.

3.2.1 **Reference Variable**

The first step of EWS is to identify the reference variable of what the EWS wants to early signal or to forecast. The research aims to early warn the fluctuation of economic activities deviating from its long-run potential or Economic Cycle (EC) based on the growth cycle concept. The indicators commonly used to identify EC are Real Gross Domestic Product (GDP) and Manufacturing Production Index (MPI). However, MPI might not be appropriate as the proxy for economic activities for all nations because, in some cases, it acts as a leading not coincident indicator of EC (Worg, S. (2014) as cited in Bilan et al., 2017). Therefore, the study employs GDP as a reference series of the Thai economy to identify EC.

3.2.2 **Composite Leading Indexes and their Components**

The research constructs CLIs from leading indicators of EC, which represent the real sector, the financial sector, the monetary sector, and the global sector. These CLIs will be separated into three groups depending on their leading performance of the EC, including short-term, medium-term, and long-term leading periods. The number of indicators to form the CLIs are both single-item measure and multiple-item measure. Based on the literature review, the CLIs and their components show as the following:

3.2.2.1 Short-Term CLI

A short-term CLI in the research refers to the CLIs that tend to signal 1-3 quarters before the EC fluctuation. The research constructs two short-term CLIs as follows.

1) **Short-Leading Economic Index (SLEI):** SLEI is CLI aiming to notice the fluctuations of EC in the short-term. The research

constructs it from Narrow Money (M1), Business Sentiment Index (next three months) (BSI), and Export Volume Index (excluding gold) (EX), which are parts of the short-term leading economic's component used by Bank of Thailand (n.d.).

2) **International Transmission by Trade Channel (ITT):** ITT represents the global economic transmission to Thailand by the trade channel. Thailand is a small open economy, which has significant revenue from exportation. Because of the reliance on demand for Thai goods and services from partner economies, the economic fluctuations of those countries can have a spillover effect on Thailand through the trade channel. Therefore, the research considers applying the economies of the US and the major five-ASIA countries (namely China, India, Indonesia, Japan, and Korea) as components of ITT because they are the major export markets of Thailand (the US and the major five-ASIA countries have a market share about 11.0% and 30.0% of the total Thai exportation in 2018, respectively). As mentioned, the demand happens before the exportation; hence, the study applies CLI for major five Asia (FiveAsia_CLI) and CLI for the United States (USA_CLI) to be the proxy variable of ITT.

3.2.2.2 Medium-Term CLI

The medium-term CLI in the research refers to the CLI that tends to signal 4-8 quarters before the fluctuation of EC. The proposed model includes one medium-term CLI that is a Financial Cycle (FC) as the following.

Financial Cycle (FC): FC aims to capture the instability of the financial sector (Grinderslev et al., 2017). The research constructs FC from Housing Price Index (townhouse and land) (HPI), Household Debt to GDP (HD_GDP), and Household Debt (HD) Borio et al. (2018); (Drehmann et al., 2012; Warapong Wongwachara et al., 2018).

3.2.2.3 Long-Term CLI

The long-term CLI in the research refers to the CLIs that tend to signal nine quarters or more before the fluctuation of EC. There are two CLIs for the long-term leading period in the research as follows.

1) **Monetary Condition (MC):** The purpose of constructing the MC is to assess the stance of monetary policy (Ericsson et al., 1998). Memon and Jabeen (2018). Following Freedman (1996); Memon and Jabeen (2018), the research constructs MC from the combination of the Policy Interest Rate (IR) and the Real Effective Exchange Rate (ER).

2) **International Transmission by International Monetary Policy Channel (ITM):** ITM is the proxy of the effect from the global economy transmitting to Thailand via international monetary policy. The research represents ITM by the single-item measure, which is OECD CLI (OECDplus_CLI). It is the CLI for both member and non-member countries of OECD, which can give early signals of the world economic activity's turning points (Nilsson, 2006).

3.3 Conceptual Framework and Hypotheses

According to the literature in Chapter 2, there is the synchronization of the economic sectors. They are both domestic and international sectors, which possibly are the CLIs of EC. Hence, this section aims to provide the conceptual framework and hypothesis regarding those synchronizations in order to forecast EC.

Regarding the conceptual framework, the monetary policy measured by MC will firstly make an impact on FC ($H_{MC, FC}$), and FC will consequently impact EC ($H_{FC, SLEI}$; $H_{FC, EC}$) (Juselius, Borio, Disyatat, & Drehmann, 2017). Generally, MC appears counter-cyclical to EC ($H_{MC, SLEI}$ and $H_{MC, EC}$), referring to the study of Buckle, Kunhong, and McClellan (2003). In the short-term, there are also some signals before the turning point of EC; SLEI provides those signals ($H_{SLEI,\ EC}$) (Babecký et al., 2013; Bank of Thailand, n.d.; Gyomai & Guidetti, 2012). Moreover, the domestic economy probably gets an impact from the global economy through IT by trade channel: ITT($H_{ITT,\ SLEI}$; $H_{ITT,\ EC}$) and International monetary policy channels: ITM ($H_{ITM,\ MC}$; $H_{ITM,\ FC}$; $H_{ITM,\ SLEI}$; $H_{ITM,\ EC}$).

According to the scrutinized literature reviews, the SLEI, FC, MC, ITT, and ITM have the potential to be CLIs of EC. Therefore, the research proposes the conceptual model explaining the linkages between those CLIs and their components to predict EC as in Figure 3.2. To further contribute to the debate, there are hypotheses as follows.

Hypothesis1 $MC \rightarrow EC$ (-): MC is a long-term CLI, which is the counter-cyclical behavior of EC. (Tightening the monetary policy will have a significant negative impact on EC with direct and/or indirect effects in the next 9-12 quarters)

Hypothesis2 $FC \rightarrow EC$ (-): FC is a medium-term CLI, which is the counter-cyclical behavior of EC. (The increasing of the financial instability will have a significant negative impact on EC with direct and/or indirect effects in the next 4-8 quarters)

Hypothesis3 $ITT \rightarrow EC$ (+): ITT is a short-term CLI, which is the pro-cyclical behavior of EC. (The economic fluctuations of Thailand's export partners will have a significant impact on EC by trade channel with direct and/or indirect effects in the next 1-3 quarters)

Hypothesis4 $ITM \rightarrow EC$ (+): ITM is a long-term CLI , which is the pro-cyclical behavior of EC. (Variations in the global economy can significantly transmit to EC via the monetary sector with direct and/or indirect effects in the next 9-12 quarters)

Hypothesis5 $SLEI \rightarrow EC$ (+): SLEI is a short-term CLI , which is the pro-cyclical behavior of EC. (The changing of SLEI has a significant positive impact on EC with direct and/or indirect effects in the next 1-3 quarters)

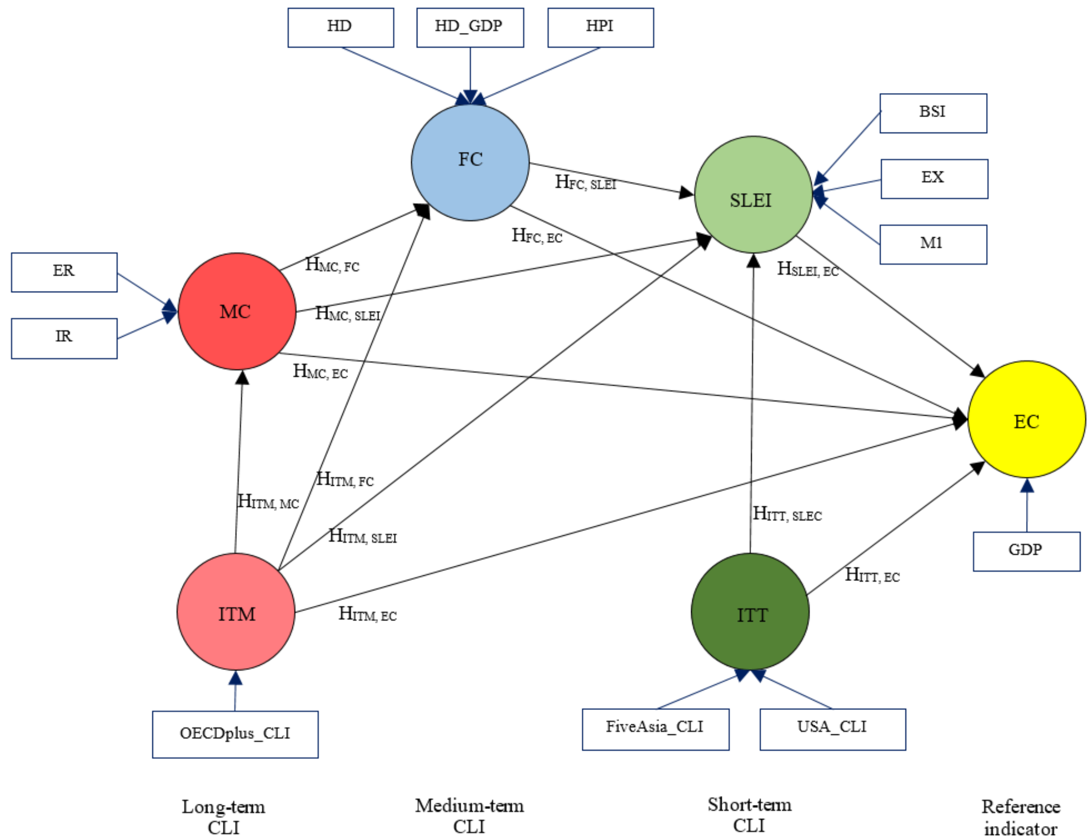


Figure 3.2 Conceptual Model

Figure 3.2 is a conceptual framework to develop the EWS from the relationship of CLIs. These CLIs are assumed to forecast EC at significantly different periods. Nevertheless, this proposed model might not be the perfect model because it might not meet the criterion for model evaluation in PLS-SEM. For instance, some paths in the conceptual model might not be significant, and the model might not be parsimonious.

3.4 Data and Data Sources

Based on the conceptual framework, the research employs various economic variables related to the Thai economy in quarterly frequency from many sources (Table 3.1-3.2). All those indicators are time-series data, which are continuous variables. Because of the limitation of available data, the study utilizes the data during Q1/2003-Q4/2018: 16 years or 64 quarters.

Even though the data is quite a short time series, it still meets the sample size requirement in PLS-SEM: the ten times rule. Regarding the formative measurement model, the sample size should be at least ten times the largest number of indicators building up the particular CLI. While considering the structural model, the size of data should be at least ten times the largest number of paths pointing at a particular construct (Barclay et al., 1995).

According to the proposed model in Figure 3.2, FC and SLEI are the formative constructs in the models with the highest number of indicators pointing to them: 3 indicators. Whereas, five paths direct at EC, which is the maximum number of paths pointing the construct. Hence, the proposed model requires at least 50 observations.

Table 3.1 Summary of Variables and Their Definitions

Variables	Descriptions
EC	**Economic Cycle** is the fluctuations in economic activities of Thailand deviating from its long term potential level.
SLEI	**Short-Leading Economic Index** is the CLI aiming to notice the fluctuations of Thai EC in the short-term. It is the combination of short-term leading indicators.
FC	**Financial Cycle** intents to capture the instability of Thailand's financial sector.
MC	**Monetary Condition** aims for assessing the stance of Thailand's monetary policy.
ITT	**International Transmission by Trade Channel** represents the global economic transmission to Thailand by the international trade channel.
ITM	**International Transmission by International Monetary Policy Channel** is the proxy of the effect from the global economy transmitting to Thailand by the international monetary sector.

Table 3.1 (Continued)

Variables	Descriptions
GDP	**Real Gross Domestic Product** is Thailand Gross Domestic Product at a constant price.
BSI	**Business Sentiment Index (next three months)** measures the expectations of entrepreneurs regarding the business performance of Thailand in the next three months from the present.
EX	**Export Volume Index (exclude gold)** is the index measure of the overall export (excluding gold) movement of Thailand over a specific period.
M1	**Narrow Money** is one of the various notions of the money supply of Thailand. It comprises the most liquid money liabilities that are held by money holders: currency in circulation less currency held by commercial banks and central government, plus demand deposits of money holders.
HD	**Household Debt** is loans, which are used due to the lack of flow of funds statistics of Thailand.
HD_GDP	**Household Debt to GDP** is the calculation of Household Debt as a percentage of Nominal GDP of Thailand.
HPI	**Housing Price Index (townhouse and land)** is a broad measure of the movement of house prices (townhouses and land) in Thailand.
ER	**Real Effective Exchange Rate** reflects Thai real purchasing power and productivity. An increase in REER refers to the baht appreciation against Thailand's major trading partners and competitors.
IR	**Policy Interest Rate** is the rate that The Monetary Policy Committee announced in conducting Thailand's monetary policy under the inflation-targeting framework.

Table 3.1 (Continued)

Variables	Descriptions
FiveAsia_CLI	**OECD CLI for Major Five Asia Countries** is CLI providing early signals in the short-term of turning points in business cycles for Major Five Asia Countries including China, India, Indonesia, Japan, and Korea
USA_CLI	**OECD CLI for the United States** is CLI providing early signals in the short-term of turning points in business cycles for the United States.
OECDplus_CLI	**CLI for OECD and Non-Member Economies** is CLI providing early signals in the short-term of turning points in business cycles for the global economy (including 33 OECD member countries and six major non-member economies).

Table 3.2 Variable Types and Data Sources

Variable Types	Constructs	Indicators	Data sources
Reference index	EC	GDP	National Economic and Social Development Council of Thailand (NESDC)
Short-term CLI	SLEI	M1	Bank of Thailand (BOT)
		BSI	Bank of Thailand (BOT)
		EX	Bank of Thailand (BOT)
	ITT	FiveAsia_CLI	OECD.Stat
		USA_CLI	OECD.Stat
Medium-term CLI	FC	HPI	Bank of Thailand (BOT)
		HD_GDP	Bank of Thailand (BOT)
		HD	Bank of Thailand (BOT)
Long-term CLI	MC	IR	Bank of Thailand (BOT)
		ER	Bank of Thailand (BOT)
	ITM	OECDplus_CLI	OECD.Stat

3.5 Data Preparation

3.5.1 Data Filtering and Standardization

The objective of this step is to evaluate the cyclical pattern of each indicator. The research follows the growth cycle concept, which defines the cyclical pattern as the movement in economic activities deviating up and down from the long-run potential level or fluctuating in the output-gap (Mintz, 1969). The study filters the indicators by removing their time series components such as decomposing seasonal factor and outlier by X12, extracting trend by Hodrick-Prescott, and smoothing them by Double Hodrick-Prescott so that no other factors obscure the cyclical pattern. However, many data have different units; the study needs to make a standardization for all data in order that they will not have the unit effect in the analysis. The steps mentioned above follow the OECD CLI procedures (Gyomai & Guidetti, 2012).

3.5.2 Unit Root Test

All indicators are filtered out unnecessary components and smoothed to retain only the cyclical pattern. To ensure that those filtered data will not cause a spurious relationship while analyzing PLS-SEM, which is based on Ordinary Least Square (OLS) Estimation. The research applies the Augmented Dickey-Fuller Unit Root Test (ADF) of Dickey and Fuller (1981) to test the data stationary.

3.6 EWS by PLS-SEM

To fulfill the research objectives, PLS-SEM prominently appropriates for this task because it can construct CLIs by measurement models, and evaluate the relationship among those CLIs from a structural model. Besides, there is a short time-series data available to model; the model is composed of a single-item construct and the formative concept. Hence, the research applies PLS-SEM to develop EWS as the following.

3.6.1 Measurement Models

According to the conceptual model, there are six constructs: four multi-item constructs and two single-item constructs. The formative measurement models are applied to build up the multi-item constructs, including SLEI, ITT, FC, and MC. The rest two single-item constructs are ITM and EC.

3.6.1.1 Specification of the Measurement model

1) **The Multi-Item Construct:** The research constructs four multi-item CLIs by the formative measurement model: SLEI, ITT, FC, and MC. To be a proxy of the constructs' domain concept, they are constructed from the linear combination of their components as follows.

$$SLEI = \pi_{BSI} BSI + \pi_{EX} EX + \pi_{M1} M1$$
$$ITT = \pi_{FiveAsia\_CLI} FiveAsia\_CLI + \pi_{USA\_CLI} USA\_CLI$$
$$FC = \pi_{HD} HD + \pi_{HD\_GDP} HD\_GDP + \pi_{HPI} HPI$$
$$MC = \pi_{ER} ER + \pi_{IR} IR$$

2) **The Single-Item Constructs:** The model includes two single-item constructs that are EC and ITM. They can be measured their domain concept by a single indicator. The relationship between the indicator and the construct of a single-item construct is 1, which is different from the multi-item construct. Therefore, the method to evaluate the multi-item measurement model cannot apply to assess these single-item constructs.

$$EC = GDP$$
$$ITM = OECDplus\_CLI$$

3.6.1.2 Evaluation of the Measurement Model

The research evaluates the SLEI, ITT, FC, and MC which are formative constructs by considering content validity, convergent validity, indicator collinearity, and statistical significance and relevance of the formative indicators as suggested by Hair et al. (2016); Hair et al. (2019); Hair et al. (2014). The research assesses the quality of these CLIs to ensure that they can capture the domain of the considerable construct.

3.6.2 **Structural Model**

After estimating and assessing CLIs from the measurement model, the research investigates the relationship between the CLIs to forecast EC by the structural model as follows.

3.6.2.1 Specification of the Structural Model

A structural model is applied to investigate the relationships between CLIs with different leading period performance: short-term, medium-term, and long-term performance, to forecast EC. When considering the timing-sequence of constructs, the long-term CLIs (ITM and MC) will happen first so that they should be on the left-hand side of the structural model. The medium-term CLIs (FC) and short-term CLIs (SLEI and ITT) will occur later; therefore, they will be in the middle of the model next to the long-term CLIs. Finally, on the right-hand side of the structure model is EC, being the target-endogenous variable, which the model aims to forecast.

The arrows represent the relationship between CLIs and EC. The direction of the arrow explains the time sequence. For example, the long-term CLIs which happen before other constructs possibly affect the long-term, the medium-term, the short-term CLI, and also EC with a direct and indirect effect. However, short-term CLI cannot go back to make an impact on the long-term and the medium-term CLI because they are the past. Besides, the research defines ITM and ITT to be the exogenous constructs, which are the international transmission from the global effect to the country. The full structural model in the proposed model sets the following.

$$MC = \gamma_{ITM,MC} ITM + \varsigma_{MC}$$

$$FC = \beta_{MC,FC} MC + \gamma_{ITM,FC} ITM + \varsigma_{FC}$$

$$SLEI = \gamma_{ITT,SLEI} ITT + \beta_{FC,SLEI} FC + \beta_{MC,SLEI} MC + \gamma_{ITM,SLEI} ITM + \varsigma_{SLEI}$$

$$EC = \beta_{SLEI,EC} SLEC + \gamma_{ITT,EC} ITT + \beta_{FC,EC} FC + \beta_{MC,EC} MC + \gamma_{ITM,EC} ITM + \varsigma_{EC}$$

3.6.2.2 Evaluation of the Structural Model

The research evaluates the Structural model aiming to assess the significance of the relationship between CLIs, and the ability of EWS to predict the EC. The research considers the collinearity between constructs, the statistical significance and relevance of the path coefficients, the coefficient of determination (R^2), and the effect size (f^2).

3.6.3 **Data Analysis Tool and the Setting for PLS-SEM**

SmartPLS version 3.2.8 is employed to construct EWS by PLS-SEM. Regarding the setting to start PLS-SEM, at the first iteration to calculate the relationship in the measurement model, the research sets the initial value to be 1: the equal weight. According to the structural model weighting schemes, the path weighting is applied for the research because it can conduct for all kinds of model specifications and estimations in PLS-SEM. Moreover, it provides the highest R^2 value for endogenous constructs (Henseler et al., 2009). The research will stop the algorithm if the change value of the weight between two iterations is lower than 10^{-7}, or the iterations reach 300 rounds. Regarding the parameter significance testing, the research employs bootstrapping with 5,000 bootstrap samples.

3.6.4 **The Use of EWS by PLS-SEM**

Pursuing the objective of the EWS to forecast EC in short-term, medium-term, and long-term periods, the conceptual EWS model could be applied to satisfy the purpose as the following.

1) **Short-Term EWS:** The short-term EWS is the conceptual model that includes all CLIs: short-term, medium-term, and long-term CLIs.

2) **Medium-Term EWS:** The medium-term EWS is the part of the conceptual model, which includes only medium-term and long-term CLIs.

3) **Long-Term EWS:** The long-term EWS is the part of the conceptual model, which includes only long-term CLIs.

3.7 Evaluation of Forecasting Performance of EWS by PLS-SEM

This section aims to evaluate the forecasting performance of EWS by PLS-SEM. To pursue this purpose, the research estimates the benchmark models: The individual CLIs with equal weight and the ARIMA model. The forecasting results from those benchmark models will be subsequently compared with the EWS's forecasting result.

3.7.1 Comparison of Forecasting Result between EWS by PLS-SEM and Equal-Weighted CLI

The comparison of the forecasting result between EWSs by PLS-SEM and equaled-weight CLIs aims to investigate whether the linkages of CLIs in the form of a structural model to forecast EC outperforms the individual CLI. The research answers the question by conducting the following.

3.7.1.1 Construction of Equal-Weighted CLI

The research constructs the individual CLIs with equal weight from the same set of indicators in EWS by PLS-SEM: considering their leading performance. The research estimates seven CLIs that are constructed from the indicators like the following.

1) Short-term CLI

CLI1 consists of 3 components including BSI, EX, and M1

CLI2 consists of 2 components including FiveAsia_CLI and USA_CLI

CLI3 consists of 5 components including BSI, EX, M1, FiveAsia_CLI, and USA_CLI

2) Medium-term CLI

CLI4 consists of 3 components including HD, HD_GDP, and HPI

3) Long-term CLI

CLI5 consists of 2 components including ER and IR

CLI6 consists of 1 component including OECDplus

CLI7 consists of 3 components including ER, IR, and OECDplus_CLI

Those seven equal-weighted CLIs will be constructed from the formula as follows.

$$equal-weighted\ CLI = \frac{\sum_{i=1}^{n} Indicator_i}{n}$$

Where

Indicator represents the component i of a considering CLI.

n represents the number of components to construct a considering CLI.

3.7.1.2 Comparison of Forecasting Performance between EWS by PLS-SEM and Equal-Weighted CLI

A cross-correlation structure and the Root Mean Square Error (RMSE) are taken to compare the forecasting performance between EWSs by PLS-SEM and the individual CLIs with equal weight.

1) **Cross-Correlation Structure:** The cross-correlation analysis is a lead-lag approach between EC and EC^f : EC^f is the forecasting value of EC from EWS by PLS-SEM and individual CLIs; the research lets EC_t^f shift by k period, i.e. EC_{t-k}^f .

The correlation analysis is applied to compare the performance of the EWSs by PLS-SEM and individual CLIs with the two subjects: the leading period and the correlation at that leading period. The research analyses the correlation coefficient (ρ) between EC and EC^f with 12 quarters forward and backward. The cross-correlation function is defined as a function of lead-lag k as follows.

$$\rho_{EC_t, EC_{t-k}} = \frac{Cov(\mathrm{EC}_t, EC_{t-k}^f)}{\sqrt{Var(\mathrm{EC}_t)\,\mathrm{Var}(EC_{t-k}^f)}}$$

Where

EC represents the economic cycle.

EC^f represents forecasting result from the model.

t represents time.

k represents lead-lag time, $k = 0, \pm 1, \pm 2, ..., \pm 12$.

The potential tools need to have a high correlation and $k > 0$, which means that those have the potential to lead the EC(Tule, Ajilore, & Ebuh, 2016).

2) **Root Mean Square Error (RMSE):** The research also considers RMSE to compare EC with the forecasting result of EC (EC_t^f) from both EWSs by PLS-SEM and individual CLIs.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{t}(EC_t^f - EC_t)^2}{t}}$$

Where

EC represents the economic cycle.

EC_t^f represents the forecasting of EC_t .

t represents time.

3.7.2 **Comparison of Forecasting Result between EWS by PLS-SEM and ARIMA Model**

The research also compares the forecasting performance of EWSs by PLS-SEM to the Autoregressive Integrated Moving Average (ARIMA) models. The research selects the ARIMA model as a benchmark because it is popular in the forecasting task, especially for short-term forecasting. Besides, in some cases, the results of this method are more reliable than those obtained from the traditional model (Gujarati, 2003).

3.7.2.1 Construction of the ARIMA model

Box and Jenkins (1976) proposed the Box-Jenkins method, which is known as an ARIMA model. The model constructs from the probabilistic or stochastic properties of time series data, which forecast the data by their past or lagged value and their stochastic error term. It is an iterative process to identify a possible model from a general class of models; the process is repeated until the model meets expectations. The selected model will be assessed against the historical data to see whether it accurately describes the series. It will be considered as a satisfactory model if the residuals between the forecasting data and the historical data are small discrepancies, randomly distributed, and independent.

ARIMA is a general class of Box-Jenkins models for stationary data. An autoregressive process (AR) forecasts EC_t from a function of the actual past value of EC_t, whereas a moving average process (MA) forecasts EC_t from a function of the past error terms. An autoregressive and moving average process (ARMA) and an autoregressive integrated moving average process (ARIMA) forecast EC_t from a function of the actual past value of EC_t and the past error terms. $ARIMA(p,d,q)$ represents the ARIMA model as follows.

$$EC_{tt}^{*} = \alpha + \beta_1 EC_{t-1}^{*} + \ldots + \beta_p EC_{t-p}^{*} + \mu_t - \theta_1 \mu_{t-1} - \ldots - \theta_q \mu_{t-q}$$

$$EC_t^{*} = \Delta^d EC_t$$

Where

AR represents an autoregression.

MA represents a moving average.

I represents an integration.

p represents an order of autoregression.

d represents an order of integration.

q represents an order of moving average.

β represents an autoregression parameter.

θ represents a moving average parameter.

t represents time.

EC represents the economic cycle.

3.7.2.2 Comparison of Forecasting Performance between EWS by PLS-SEM and the ARIMA Model

The research compares the forecasting performance of EWSs by PLS-SEM to the ARIMA models by considering RMSE and the correct sign prediction. Both the EWS by PLS-SEM and the ARIMA are estimated from sub-sample data by an increasing window rolling approach to evaluate the out of sample forecasting performance.

1) **Increasing Window Rolling Approach:** The research estimates EWSs by PLS-SEM and ARIMA models from sub-sample data by an increasing window rolling approach, and subsequently forecasts out-of-sample data. Regarding the sub-sample from an increasing window rolling approach, the first of a rolling window is size m, which is the number of observations for the first sub-sample, and the second sub-sample will add more a new observation, and so on as in Figure 3.3.

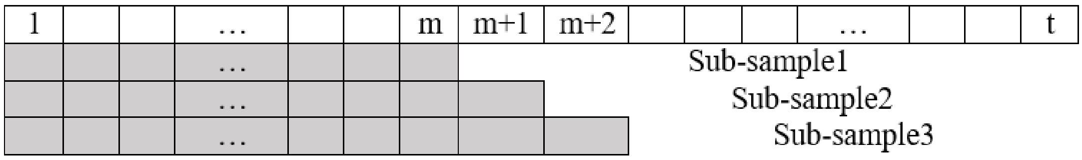


Figure 3.3 Increasing Window Rolling Sub-Sample

For example, the first sub-sample of the research includes data 2003Q1-2013Q4, and the second sub-sample will add a new observation as for 2003Q1-2014Q1, and so on, the last sub-sample includes 2003Q1-2016Q4. Both the EWSs by PLS-SEM and ARIMA models are estimated from those sub-samples to forecast out-of-sample data: 2014Q1-2016Q3, 2014Q2-2016Q4,…, and the last one forecasts 2017Q1-2019Q3.

2) **Correct Sign Prediction:** The concept of correct sign prediction is applied from the confusion matrix of Townsend (1971). The confusion matrix is a simple cross-tabulation reporting the results of classification performance. It provides the relations between the classifier forecasting and the actual values. As for correct sign prediction, the study considers two stages of EC; prosperity (EC is above zero), depression (EC is equal to or less than zero) (Figure 3.4). It will be considered the correct signal if the forecasting result

from EC^f signals the same as the signal of EC. The better model must have a higher percentage of the correct sign prediction.

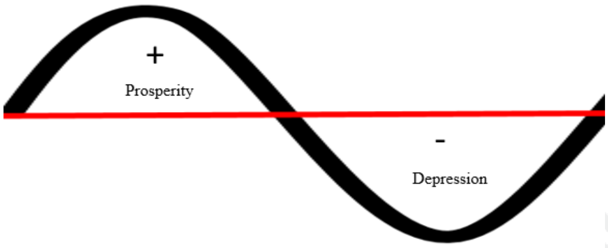


Figure 3.4 Prosperity and Depression of EC

Table 3.3 Correct Sign Prediction

		EC	
		Prosperity (>0)	Depression (≤ 0)
EC_t^f	Prosperity (>0)	A	B
	Depression (≤ 0)	C	D

$$\%\ of\ \ correct\ sign\ prediction = \frac{A+D}{A+B+C+D}$$

Where

A is the number of times in which $EC^f > 0$ and $EC > 0$.

B is the number of times in which $EC^f > 0$ and $EC \leq 0$.

C is the number of times in which $EC^f \leq 0$ and $EC > 0$.

D is the number of times in which $EC^f \leq 0$ and $EC \leq 0$.

CHAPTER 4

RESEARCH RESULTS

The development of the Early Warning System (EWS) to forecast the Economic Cycle (EC) is presented in this chapter. It provides the results of PLS-SEM and the comparison of the forecasting performance between the EWS by PLS-SEM and the benchmark models as the following topics.

4.1 Identification of Cyclical Pattern for Indicators
4.2 Development of EWS by PLS-SEM
4.3 Comparison of Forecasting Performance between EWS by PLS-SEM and the Benchmark Models

4.1 Identification of Cyclical Pattern for Indicators

The research applies Real Gross Domestic Product (GDP) as the proxy of the Thai economy, which is the target variable that the EWS aims to early signal or to forecast. The indicators from various economic sectors are gathered to construct CLIs based on the literature review, to represent the real sector, the financial sector, the monetary sector, and the global sector. Those indicators are continuous variables. Because of the limitation of available data, the study utilizes the data from Q1/2003 to Q4/2018; 16 years or 64 quarters. According to the proposed model in Figure 3.2 in Chapter 3, the analysis needs at least 50 observations to meet the sample requirement of PLS-SEM: the 10-time rules of Barclay et al. (1995).

A subsequence of gathering needed datasets, the research identifies the cycle pattern of each indicator. Following the OECD CLI procedure, first, the research filters out the unneeded components for all indicators in order to retain only the cyclical pattern by X12 and Double Hodrick-Prescott, and then standardizes them to resolve the problem of the unit effect (Gyomai & Guidetti, 2012). Figure 4.1 presents the raw and filtered datasets.

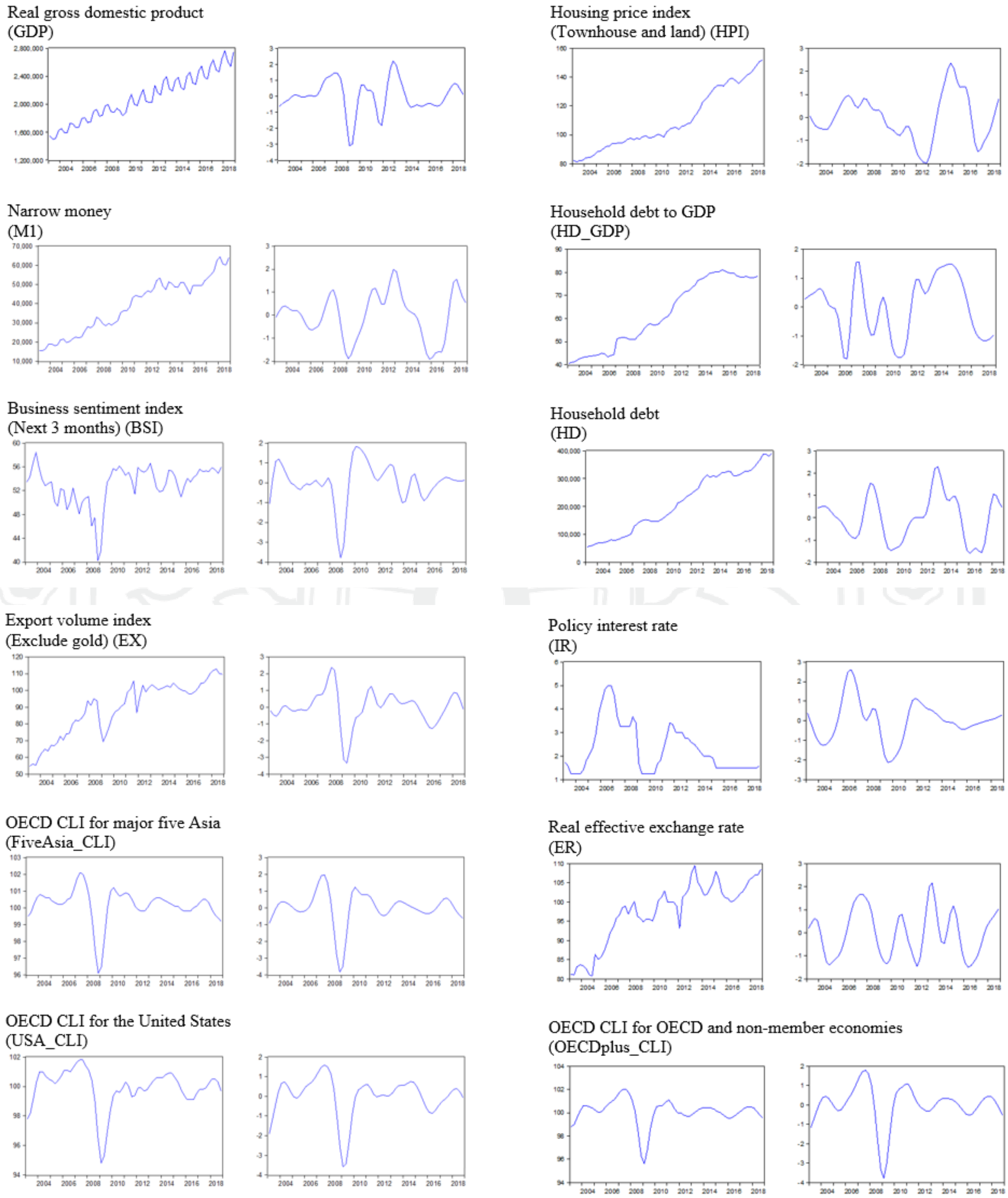


Figure 4.1 Plot of Raw Data and Filtered Data

Typically, the filtering process will transform data to be stationary by their construction. Besides, the results of the Augmented Dickey-Fuller Unit Root Test (ADF) confirms that those filtered data do not have unit root to cause a spurious relationship when analyzing PLS-SEM based on Ordinary Least Square (OLS) estimation (Table 4.1).

Table 4.1 Results of the Augmented Dickey-Fuller unit root (ADF) Test

Indicators	Variables	t-Statistic
Real Gross Domestic Product	GDP	-5.02*
Narrow Money	M1	-4.19*
Business Sentiment Index (Next 3 months)	BSI	-2.32**
Export Volume Index (Excluding Gold)	EX	-4.05*
OECD CLI for Major five Asia	FiveAsia_CLI	-4.19*
OECD CLI for the United States	USA_CLI	-3.04*
Housing Price Index (Town House and Land)	HPI	-4.60*
Household Debt to GDP	HD_GDP	-2.98*
Household Debt	HD	-3.08*
Policy Interest Rate	IR	-3.69*
Real Effective Exchange Rate	ER	-4.24*
OECD CLI for OECD and non-member economies	OECDplus_CLI	-3.83*

Note: *, **, *** significant at the 0.01, 0.05, 0.10 level respectively

4.2 Development of EWS by PLS-SEM

To develop EWS by PLS-SEM, firstly, the research develops the CLIs from the formative measurement models, including SLEI, FC, MC, ITT, while the research sets ITM as a single-item construct. Each construct represents each CLI of EC based on the literature review. Subsequently, the analysis estimates the relationships between CLIs by the structural model

4.2.1 **Construction of CLIs and Investigation of Their Leading Periods**

Regarding the conceptual model, the research constructs five CLIs: SLEI, FC, MC, and ITT with multi-item constructs, and ITM with a single-item construct. These CLIs are separated into three groups: short-term, medium-term, and long-term leading periods; however, the research needs to investigate how many quarters they can signal EC fluctuation in advance. Thus, the research roughly identifies those CLIs-leading periods by constructing each CLI with a formative measurement model from their indicators at k leading period (k=1,...,12) to EC (Estimated from 64-12=52 observations). For this purpose, the research considers only k that produces absolute correlation ($|R|$) between $CLI_{t-k} \rightarrow EC_t$ higher than 0.70 or R^2 at least 0.50 because it implies that the considering CLI at those k leading periods can explain the variation of EC at least 50% (Figure 4.2).

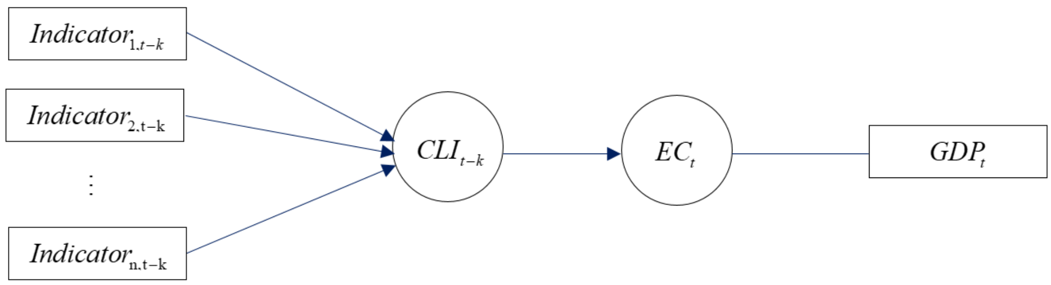


Figure 4.2 Conceptual Model to Investigate the Leading Period of CLIs to EC

The result in Table 4.2 exhibits the possible leading period of each CLI at k periods. Regarding the short-term CLIs, $SLEI_{t-k}$ and ITT_{t-k} have a maximum R^2 at k=1, which are 0.53 and 0.50 so that $SLEI_{t-k}$ and ITT_{t-k} can lead EC_t one-period ahead (k=1). Considering the medium-term CLIs, the maximum R^2 of FC_{t-k} is 0.50 at k=7; therefore, FC_{t-k} tends to lead EC_t seven periods ahead (k=7). According to the long-term CLIs, MC_{t-k} produce R^2 at least 0.50 at k=5, 11, and 12, which implies that it possibly leads EC_t at five, eleven, or twelve-periods. Regarding the conceptual model from Figure 3.2 in Chapter 3, MC_{t-k} is the long-term CLI of which the leading period should be longer than FC_{t-k} and be at least nine quarters; hence, the research considers k of MC_{t-k} only 11 and 12.

Interestingly, ITM_{t-k} does not have any k periods, which produces R^2 between $ITM_{t-k} \rightarrow EC_t$ at least 0.50; hence, it implies that ITM_{t-k} could not lead EC_t directly. However, ITM_{t-k} possibly lead EC_t indirectly through MC_{t-k} because $ITM_{t-11} -> MC_{t-11} -> EC_t$, $ITM_{t-12} -> MC_{t-12} -> EC_t$, and $ITM_{t-12} -> MC_{t-11} -> EC_t$ create R^2 at 0.51, 0.50, and 0.71, respectively.

Table 4.2 Results of the Investigation of CLIs' Leading Period to EC

CLI_{t-k}	k leading period that gives $R^2 \geq 0.5$
$SLEI_{t-k} \rightarrow EC_t$	k=1, R^2=0.53
$ITT_{t-k} \rightarrow EC_t$	k=1, R^2=0.50
$FC_{t-k} \rightarrow EC_t$	k=7, R^2=0.50
$MC_{t-k} \rightarrow EC_t$	k=5, R^2=0.60
	k=11, R^2=0.54
	k=12, R^2=0.60

Before estimating EWS by PLS-SEM, the research evaluates $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, MC_{t-11}, and MC_{t-12}, which are CLIs constructed from formative measurement models, by assessing the convergent validity, indicator collinearity, and statistical significance and relevance. The evaluations aim to ensure that those CLIs can signal EC_t effectively (this section estimated from 64-12=52 observations).

Convergent Validity: The research firstly evaluates the convergent validity to confirm that each CLI can capture the total domain of the construct through redundancy analysis. The study applies the method of Sarstedt et al. (2013), who proposes to use an alternative-single item that can recap the core concept of the formative construct. The conclusion of convergent validity exhibits when the CLI and the alternative measure show $|R| \geq 0.70$ or $R^2 \geq 0.50$ (Hair et al., 2016; Hair et al., 2019).

Since the purpose of all CLIs is to signal ahead of EC_t, the research applies EC_t as the alternative-single item as shown in Figure 4.3. The results of R^2 between $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, MC_{t-11} and MC_{t-12} to EC_t are 0.53, 0.50, 0.50, 0.54, and 0.60, which exhibit convergent validity because they can explain the variation of EC_t at least 50%. Therefore, it can infer that those CLIs show the ability to advance signal EC.

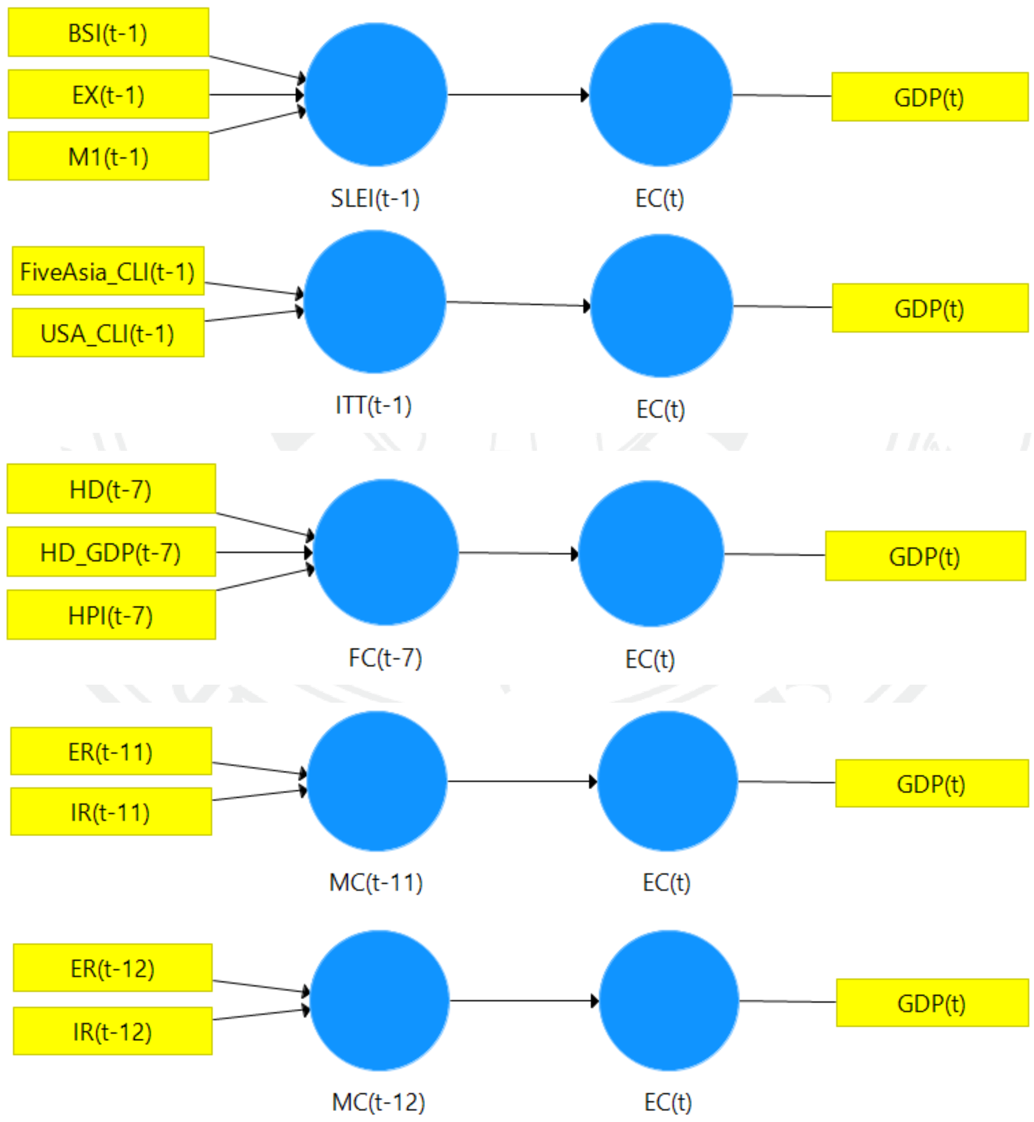


Figure 4.3 Redundancy Analysis: Assessing the Formative Measurement Model of Each CLI

Indicator Collinearity: Variance Inflation Factor (VIF) is taken to verify whether the collinearity problem exhibits among leading indicators in the same CLI. The result confirms that there is no collinearity problem because all of the VIF values are under the threshold at 5.00 (Table 4.3).

Table 4.3 Results of Assessing the Collinearity Problem by Variance Inflation Factor (VIF) of each CLI before Estimating the EWS by PLS-SEM

CLI_{t-k}	Variables	VIF for the measurement model
$SLEI_{t-1}$	BSI_{t-1}	1.25
	EX_{t-1}	2.26
	$M1_{t-1}$	2.61
ITT_{t-1}	$FiveAsia\_CLI_{t-1}$	2.50
	USA_CLI_{t-1}	2.50
FC_{t-7}	HD_{t-7}	1.27
	HD_GDP_{t-7}	1.41
	HPI_{t-7}	1.14
MC_{t-11}	ER_{t-11}	1.14
	IR_{t-11}	1.14
MC_{t-12}	ER_{t-12}	1.14
	IR_{t-12}	1.14

Statistical Significance and Relevance: Bootstrapping is employed to test the weight significance of each indicator to their construct. The result shows that many of them are significant, which means that they are relatively important to CLI. Nevertheless, M_{t-1} of $SLEI_{t-1}$, and HD_{t-7} of FC_{t-7} are not significant, but the research still retains them in the model because their loadings are high (≥ 0.50), which implies that they are of absolute importance for their construct (Table 4.4).

Table 4.4 Results of Assessing Weight Significance in Formative Indicators

Indicator $\rightarrow$ CLI	Weight significance of the indicators				
	Original Sample	Sample Mean	Standard Deviation	t Statistics	Loading
$BSI_{t-1} \rightarrow SLEI_{t-1}$	0.69	0.66	0.12	5.59*	0.87
$EX_{t-1} \rightarrow SLEI_{t-1}$	0.33	0.33	0.19	1.74***	0.68
$M1_{t-1} \rightarrow SLEI_{t-1}$	0.23	0.24	0.21	1.06	0.77
$FiveAsia\_CLI_{t-1} \rightarrow ITT_{t-1}$	0.64	0.59	0.20	3.14***	0.96
$USA\_CLI_{t-1} \rightarrow ITT_{t-1}$	0.42	0.46	0.20	2.15**	0.92
$HD_{t-7} \rightarrow FC_{t-7}$	0.25	0.24	0.17	1.51	0.64
$HD\_GDP_{t-7} \rightarrow FC_{t-7}$	0.90	0.90	0.12	7.59*	0.95
$HPI_{t-7} \rightarrow FC_{t-7}$	-0.21	-0.22	0.12	-1.75***	0.07
$ER_{t-11} \rightarrow MC_{t-11}$	-0.18	-0.19	0.10	-1.80***	0.20
$IR_{t-11} \rightarrow MC_{t-11}$	1.05	1.05	0.04	25.96*	0.99
$ER_{t-12} \rightarrow MC_{t-12}$	-0.20	-0.20	0.12	-1.67***	0.17
$IR_{t-12} \rightarrow MC_{t-12}$	1.05	1.05	0.04	27.63*	0.98

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

4.2.2 EWS Development: Model Specification

The result of assessing CLIs from Section 4.2.1 ensures that those CLIs can advance signal EC_t. The research specifies the proposed model: with possible k leading periods. There are three possible models shown in Figure 4.4 to Figure 4.6. The first model (Figure 4.4) is composed of $SLEI_{t-1}, ITT_{t-1}, FC_{t-7}, MC_{t-11}$, and

ITM_{t-11}, which estimate the Coefficient of Determination (R^2) at 0.87 (estimated from 64-11=53 observations), whereas the second model (Figure 4.5) is estimated from $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, MC_{t-12}, and ITM_{t-12}, which produces R^2 at 0.80 (estimated from 64-12=52 observations). The last model (Figure 4.6), which is constructed from $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, MC_{t-11}, and ITM_{t-12}, has R^2 at 0.82 (estimated from 64-12=52 observations). Considering R^2, the first model in Figure 4.4 is more prominent than the others.

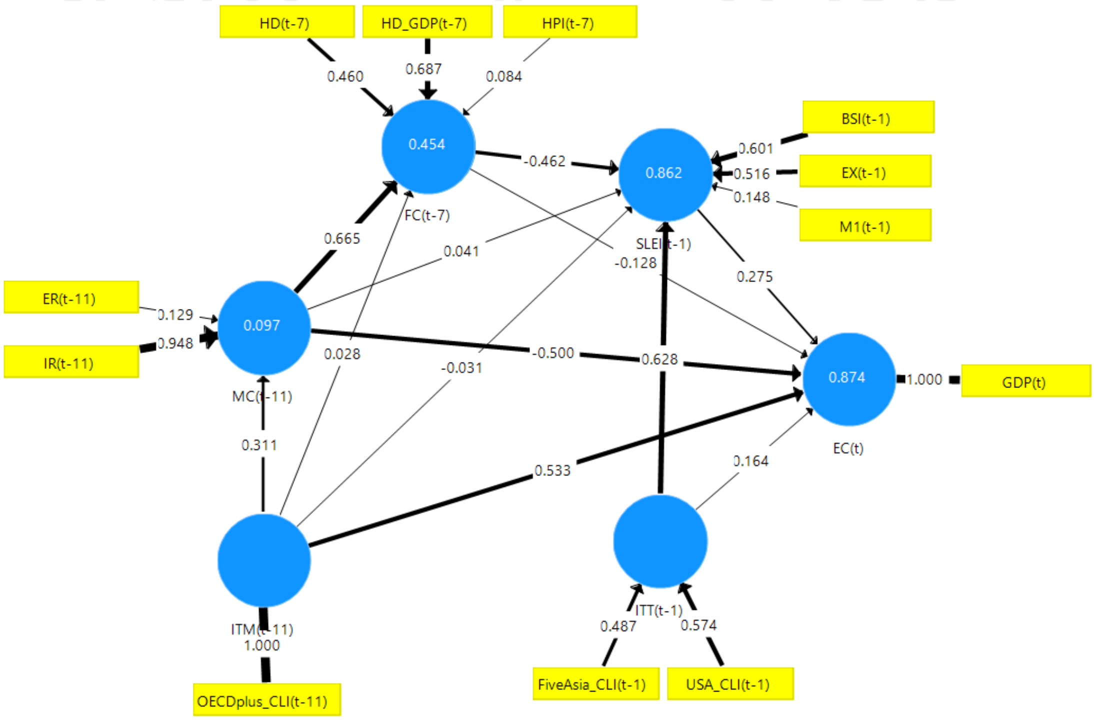


Figure 4.4 The First Model of the Three Possible EWS by PLS-SEM

Note: R^2 values are in the circles and weights/path coefficients are on the lines

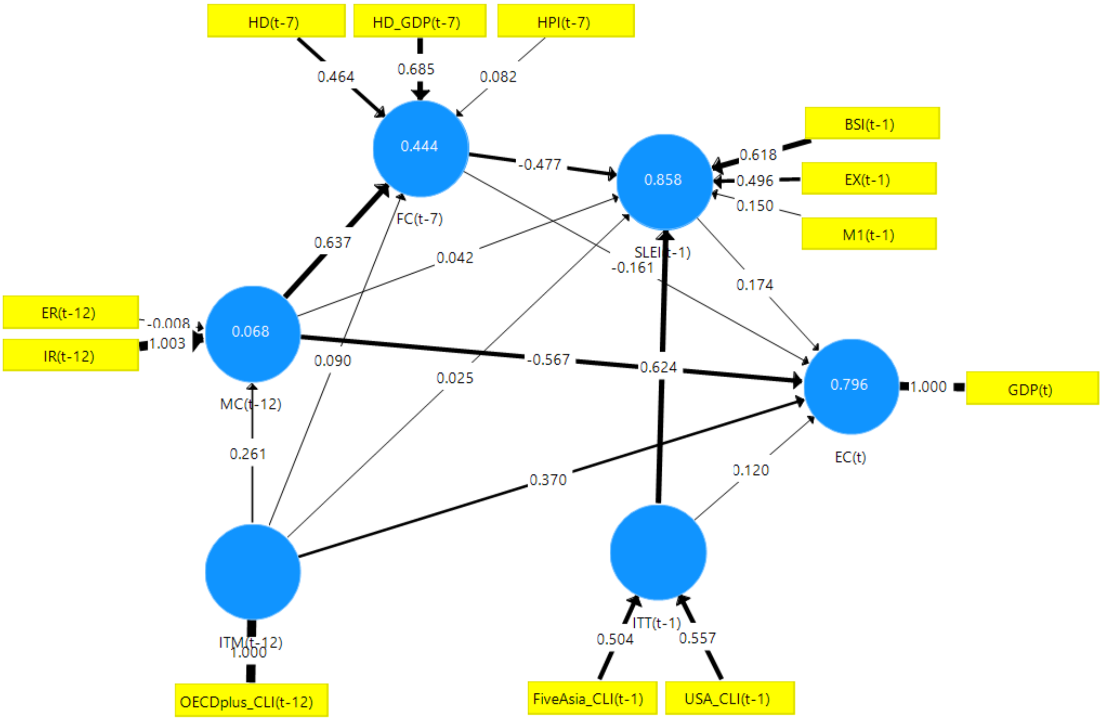


Figure 4.5 The Second Model of the Three Possible EWS by PLS-SEM

Note: R^2 values are in the circles and weights/path coefficients are on the lines

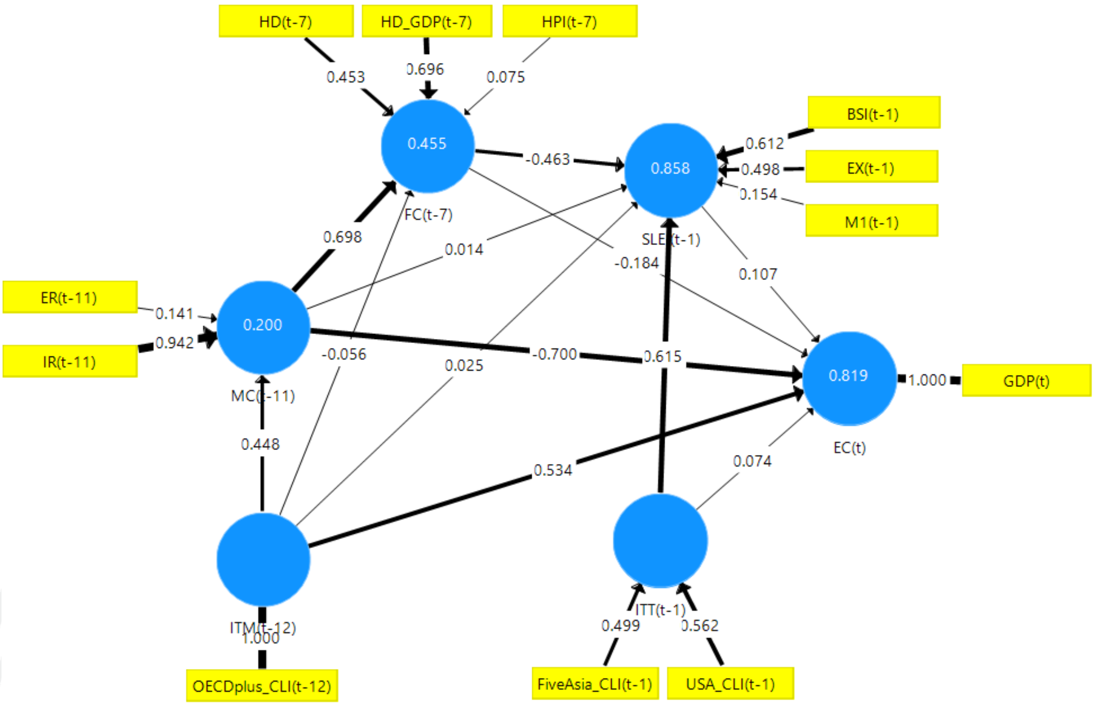


Figure 4.6 The Third Model of the Three Possible EWS by PLS-SEM

Note: R^2 values are in the circles and weights/path coefficients are on the lines

Even though the first model in Figure 4.4 (composed of CLIs including $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, MC_{t-11}, and ITM_{t-11}) is outstanding because it produces the highest R^2 at 0.87. However, some path coefficients in the model are not statistically significant. Therefore, the research eliminates those paths to develop EWS model as in Figure 4.7. The result of the parsimonious model, which is estimated from 54-11=53 observations, shows R^2 at 0.87.

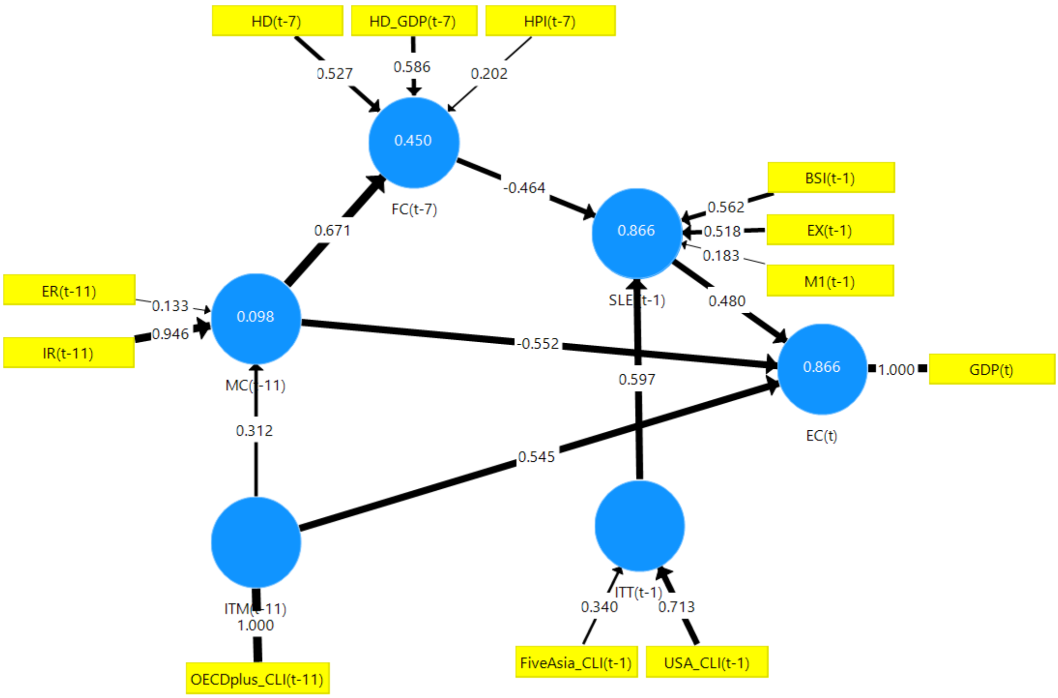


Figure 4.7 EWS by PLS-SEM to Forecast EC

Note: R^2 values are in the circles and weights/path coefficients are on the lines

4.2.3 EWS Assessment: Evaluation of the PLS-SEM Result

Regarding EWS by PLS-SEM from Figure 4.7, the research assesses PLS-SEM output, both the formative measurement models and the structural model (estimated from 64-11=53 observations).

4.2.3.1 Assessment of the CLIs in EWS: Evaluation of the Formative Measurement Model

The CLIs in the EWS include $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, and MC_{t-11}, which are built up from a formative multi-item construct. The research ensures these CLIs can advance signal EC by evaluating the convergent validity, indicator collinearity in the CLI, and statistical significance and relevance of the formative indicators.

Convergent Validity: Assessing the convergent validity of each CLI in EWS to confirm that each CLI can capture the total domain of the construct and all of its essential facets through redundancy analysis. CLIs in EWS aim to forecast or advance signal EC_t; therefore, EC_t is applied to be the alternative-single item to assess convergent validity as the method of Sarstedt et al. (2013). The results show that all formative measurement constructs including $SLEI_{t-1}$, ITT_{t-1}, FC_{t-7}, and MC_{t-11} have $R^2 \geq 0.50$ with EC_t at 0.52, 0.50, 0.50, and 0.53. Therefore, it can infer that those CLIs exhibit the ability to advance signal EC because they can explain the variation of EC_t at least 50% (Table 4.5).

Table 4.5 Results of Assessing the Convergent Validity for Formative Measurement Models by Redundancy Analysis

CLI_{t-k}	R^2 between CLI_{t-k} and EC_t
$SLEI_{t-1} \rightarrow EC_t$	0.52
$ITT_{t-1} \rightarrow EC_t$	0.50
$FC_{t-7} \rightarrow EC_t$	0.50
$MC_{t-11} \rightarrow EC_t$	0.53

Indicator Collinearity: Considering the Variance Inflation Factor (VIF), it can conclude that there is no collinearity problem exhibited in the formative measurement models because of all VIF values under the threshold at 5.00 (Table 4.6).

Table 4.6 Results of Assessing the Collinearity Problem in Formative Measurement Models by Variance Inflation Factor (VIF)

CLI_{t-k}	Variables	VIF for the measurement model
EC_t	GDP_t	1.00
$SLEI_{t-1}$	BSI_{t-1}	1.25
	EX_{t-1}	2.26
	$M1_{t-1}$	2.61
ITT_{t-1}	$FiveAsia\_CLI_{t-1}$	2.50
	USA_CLI_{t-1}	2.50
FC_{t-7}	HD_{t-7}	1.27
	HD_GDP_{t-7}	1.40
	HPI_{t-7}	1.14
MC_{t-11}	ER_{t-11}	1.14
	IR_{t-11}	1.14
ITM_{t-1}	$OECDplus\_CLI_{t-11}$	1.00

Statistical Significance and Relevance of the Formative Indicators: The test of weight significance is employed from bootstrapping. Regarding Table 4.7, most of the indicators are significant, which means that they are relatively important to the construct. Nevertheless, M_{t-1} of $SLEI_{t-1}$, and ER_{t-11} of MC_{t-11} are not significant, the research still retains them in the model because their loadings are high (≥ 0.50), which implies that they are relevant to the constructs.

Table 4.7 Results of Assessing the Weight Significance in Formative Indicators

Indicator $\rightarrow$CLI	The weight significance of the indicators Original Sample	Sample Mean	Standard Deviation	t Statistics	Loading
$BSI_{t-1} \rightarrow SLEI_{t-1}$	0.56	0.55	0.13	4.46*	0.78
$EX_{t-1} \rightarrow SLEI_{t-1}$	0.52	0.52	0.12	4.28*	0.80
$M1_{t-1} \rightarrow SLEI_{t-1}$	0.18	0.19	0.14	1.36	0.81
$FiveAsia\_CLI_{t-1} \rightarrow ITT_{t-1}$	0.34	0.33	0.21	1.65***	0.89
$USA\_CLI_{t-1} \rightarrow ITT_{t-1}$	0.71	0.72	0.19	3.85*	0.98
$HD_{t-7} \rightarrow FC_{t-7}$	0.53	0.53	0.10	5.49*	0.78
$HD\_GDP_{t-7} \rightarrow FC_{t-7}$	0.59	0.59	0.09	6.204*	0.88
$HPI_{t-7} \rightarrow FC_{t-7}$	0.20	0.19	0.10	2.05**	0.37
$ER_{t-11} \rightarrow MC_{t-11}$	0.13	0.14	0.15	0.91	0.50
$IR_{t-11} \rightarrow MC_{t-11}$	0.95	0.93	0.08	11.95*	0.99

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

4.2.3.2 Assessment of the Relationship between CLIs: Evaluation of the Structural Model

The research assesses the EWS ability from the structural model: the forecasting performance, and the significance of the relationships between CLIs to forecast EC. Thus, the analysis considers the coefficient of determination (R^2), the effect size (f^2), the collinearity between constructs, and the statistical significance and relevance of the path coefficients.

The Coefficient of Determination (R^2): R^2 is the statistical value to assess the predictive power of the structural model. According to Hair et al. (2016); Hair et al. (2019); Hair et al. (2014), if R^2 value of endogenous latent variables is at least 0.75, 0.50, or 0.25, it is considered as large, moderate and weak predictive power. Nevertheless, depending on the context and case, a very low value of R^2 as 0.10 is satisfactory (Hair et al., 2019).

The result shows that the model has a substantial predictive accuracy for EC_t with the evidence of R^2=0.87 (Table 4.8). Regarding the other endogenous constructs, R^2 of EWS for $SLEI_{t-1}$, FC_{t-7}, and MC_{t-11} are 0.87, 0.45, and 0.10, respectively.

Table 4.8 Results of Assessing the Coefficient of Determination (R^2) in the Structural Model

CLI	R^2
EC_t	0.87
$SLEI_{t-1}$	0.87
FC_{t-7}	0.45
MC_{t-11}	0.10

Effect size (f^2): Assessing f^2 is the additional evaluation of R^2 to check whether the omission of the specific CLI makes substantively impact on the considering endogenous construct. If f^2 value is over 0.02, 0.15, and 0.35, it will be considered as a small, medium, and large effect size, respectively (Cohen, 1988 as cited in Hair et al., 2016; Hair et al., 2019). The evidence from Table 4.9 shows that most of them have a large size of f^2, which means that they have a substantial impact on the considering endogenous construct, except ITM_{t-11}, which makes a small impact on MC_{t-11}.

Table 4.9 Results of Assessing the Effect size (f^2) in the Structural Model

		The considering endogenous construct			
		EC_t	$SLEI_{t-1}$	FC_{t-7}	MC_{t-11}
The omission of the specific CLI	$SLEI_{t-1}$	1.00			
	FC_{t-7}		1.16		
	MC_{t-11}	1.23		0.82	
	ITT_{t-1}		2.00		
	ITM_{t-11}	2.00			0.11

Collinearity Assessment: Based on the regression procedure, the research assesses the collinearity issue to confirm that the structural model does not produce a spurious relationship among CLIs. As a similarity to assess the collinearity issue in a formative measurement model, VIF is the statistical value to assess the collinearity problem. A serious collinearity problem will occur if VIF value is above 5.00. As shown in Table 4.10, explicit that there is no severe collinearity problem between the CLIs in the structure model because there is no VIF over 5.00.

Table 4.10 Results of Assessing the Collinearity Problem in the Structural Model by Variance Inflation Factor (VIF)

$CLI_{t-k} \rightarrow EC_t$	VIF for the structural model
$SLEI_{t-1} \rightarrow EC_t$	1.78
$ITT_{t-1} \rightarrow SLEI_{t-1}$	1.39
$FC_{t-7} \rightarrow SLEI_{t-1}$	1.39
$MC_{t-11} \rightarrow EC_t$	1.86
$MC_{t-11} \rightarrow FC_{t-7}$	1.00
$ITM_{t-11} \rightarrow EC_t$	1.11
$ITM_{t-11} \rightarrow MC_{t-11}$	1.00

Statistical Significance of Path Coefficients: The results of the significance of path coefficients, indirect effects, specific indirect effects, and also total effects are shown in Table 4.11 to Table 4.14. These can conclude the hypothesis testing as follows.

The result supports the Hypothesis1: $MC \rightarrow EC$; MC is the long-term CLI of EC. The changing of MC will have an impact on EC, both direct and indirect effects. The total effect of MC on EC is -0.70, meaning that the increase of MC will cause a negative impact on EC in the next 11 quarters. On account of the Hypothesis2: $FC \rightarrow EC$, FC has an indirect effect on EC through SLEI. The total effect of FC on EC is -0.22, which infers that an increase of FC will reduce EC in the next seven quarters. Therefore, the study supports the Hypothesis2: $FC \rightarrow EC$. Evaluating the Hypothesis5: $SLEI \rightarrow EC$, SLEI has a statistically direct effect on EC. The path coefficient of SLEI on EC is 0.48, inferring that if the SLEI increases, EC will improve in the next quarter. Hence, the Hypothesis5: $SLEI \rightarrow EC$ is approved. According to International Transmission, it is separated into ITT and ITM. Starting with ITM, it significantly affects EC, both direct and indirect effects. The total effect of ITM on EC is 0.33, implying that an increase of ITM will positively affect EC in the next 11 quarters. Regarding ITT, it indirectly affects EC through SLEI with the total effect at 0.29, showing that the changing of ITT will have a positive impact on EC in the next quarter. Hence, both the Hypothesis4: $ITM \rightarrow EC$ and Hypothesis3: $ITT \rightarrow EC$ are verified. According to Table 4.11 to Table 4.14, it can be concluded that all hypotheses are supported.

Table 4.11 Results of Assessing the Significance of Path Coefficients in the Structural Model

Path Coefficients	Original Sample	Bootstrap			
		Sample Mean	Standard Deviation	t Statistics	Supported Hypothesis
$SLEI_{t-1} \rightarrow EC_t$	0.48	0.48	0.08	5.74*	H5
$MC_{t-11} \rightarrow EC_t$	-0.55	-0.55	0.07	7.98*	H1
$ITM_{t-11} \rightarrow EC_t$	0.54	0.53	0.16	3.52*	H4
$FC_{t-7} \rightarrow SLEI_{t-1}$	-0.46	-0.47	0.10	4.50*	
$ITT_{t-1} \rightarrow SLEI_{t-1}$	0.60	0.58	0.11	5.61*	
$MC_{t-11} \rightarrow FC_{t-7}$	0.67	0.68	0.07	9.63*	
$ITM_{t-11} \rightarrow MC_{t-11}$	0.31	0.31	0.13	2.33**	

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

Table 4.12 Results of Assessing the Significance of Indirect Effects in the Structural Model

Indirect Effects (Path)	Original Sample	Bootstrap			
		Sample Mean	Standard Deviation	t Statistics	Supported Hypothesis
$ITT_{t-1} \rightarrow EC_t$	0.29	0.28	0.08	3.47*	H3
$FC_{t-7} \rightarrow EC_t$	-0.22	-0.22	0.04	5.00*	H2
$MC_{t-11} \rightarrow EC_t$	-0.15	-0.15	0.03	4.84*	H1
$ITM_{t-11} \rightarrow EC_t$	-0.22	-0.21	0.10	2.27**	H4
$ITM_{t-11} \rightarrow SLEI_{t-1}$	-0.10	-0.10	0.04	2.17**	
$MC_{t-11} \rightarrow SLEI_{t-1}$	-0.31	-0.32	0.07	4.46*	
$ITM_{t-11} \rightarrow FC_{t-7}$	0.21	0.21	0.10	2.15**	

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

Table 4.13 Results of Assessing the Significance of Specific Indirect Effects in the Structural Model

Specific Indirect Effects	Original Sample	Bootstrap			
		Sample Mean	Standard Deviation	t Statistics	Supported Hypothesis
$ITT_{t-1} \rightarrow SLEI_{t-1} \rightarrow EC_t$	0.29	0.28	0.08	3.47*	H3
$FC_{t-7} \rightarrow SLEI_{t-1} \rightarrow EC_t$	-0.22	-0.22	0.04	5.00*	H2
$MC_{t-11} \rightarrow FC_{t-7} \rightarrow SLEI_{t-1} \rightarrow EC_t$	-0.15	-0.15	0.03	4.84*	H1
$ITM_{t-11} \rightarrow MC_{t-11} \rightarrow EC_t$	-0.17	-0.17	0.08	2.24**	H4
$ITM_{t-11} \rightarrow MC_{t-11} \rightarrow FC_{t-7} \rightarrow SLEI_{t-1} \rightarrow EC_t$	-0.05	-0.05	0.02	2.01**	H4
$MC_{t-11} \rightarrow FC_{t-7} \rightarrow SLEI_{t-1}$	-0.31	-0.32	0.07	4.46*	
$ITM_{t-11} \rightarrow MC_{t-11} \rightarrow FC_{t-7} \rightarrow SLEI_{t-1}$	-0.10	-0.10	0.04	2.17**	
$ITM_{t-11} \rightarrow MC_{t-11} \rightarrow FC_{t-7}$	0.21	0.21	0.10	2.15**	

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

Table 4.14 Results of Assessing the Significance of Total Effects in the Structural Model

Total Effects	Bootstrap				
	Original Sample	Sample Mean	Standard Deviation	t Statistics	Supported Hypothesis
$SLEI_{t-1} \rightarrow EC_t$	0.48	0.48	0.08	5.74*	H5
$ITT_{t-1} \rightarrow EC_t$	0.29	0.28	0.08	3.47*	H3
$FC_{t-7} \rightarrow EC_t$	-0.22	-0.22	0.05	5.00*	H2
$MC_{t-11} \rightarrow EC_t$	-0.70	-0.70	0.07	10.48*	H1
$ITM_{t-11} \rightarrow EC_t$	0.33	0.32	0.14	2.29**	H4
$ITM_{t-11} \rightarrow SLEI_{t-1}$	-0.10	-0.10	0.05	2.17**	
$FC_{t-7} \rightarrow SLEI_{t-1}$	-0.46	-0.47	0.10	4.50*	
$MC_{t-11} \rightarrow SLEI_{t-1}$	-0.31	-0.32	0.07	4.46*	
$ITT_{t-1} \rightarrow SLEI_{t-1}$	0.60	0.59	0.11	5.61*	
$MC_{t-11} \rightarrow FC_{t-7}$	0.67	0.68	0.07	9.63*	
$ITM_{t-11} \rightarrow FC_{t-7}$	0.21	0.21	0.10	2.15**	
$ITM_{t-11} \rightarrow MC_{t-11}$	0.31	0.31	0.13	2.33**	

Note: *, **,*** significant at the 0.01, 0.05, 0.10 level respectively

Considering the total effect of EC, the results from Table 4.15 exhibit that MC_{t-11} has the strongest total effect on EC_t, followed by $SLEI_{t-1}$, ITM_{t-11}, ITT_{t-1}, and FC_{t-7}. Whereas the most significant total effect of $SLEI_{t-1}$ is ITT_{t-1} following by FC_{t-7} , MC_{t-11}, and ITM_{t-11}. Regarding FC_{t-7}, MC_{t-11} has a total effect on FC_{t-7} more than ITM_{t-11}. Finally, ITM_{t-11}, which is the only exogenous construct of MC_{t-11}, has a significant total effect on MC_{t-11}.

Table 4.15 Results of Assessing the Total Effect

		The Considering endogenous construct			
		EC_t	$SLEI_{t-1}$	FC_{t-7}	MC_{t-11}
The Specific CLI	$SLEI_{t-1}$	0.48			
	FC_{t-7}	-0.22	-0.46		
	MC_{t-11}	-0.70	-0.31	0.67	
	ITT_{t-1}	0.29	0.60		
	ITM_{t-11}	0.33	-0.10	0.21	0.31

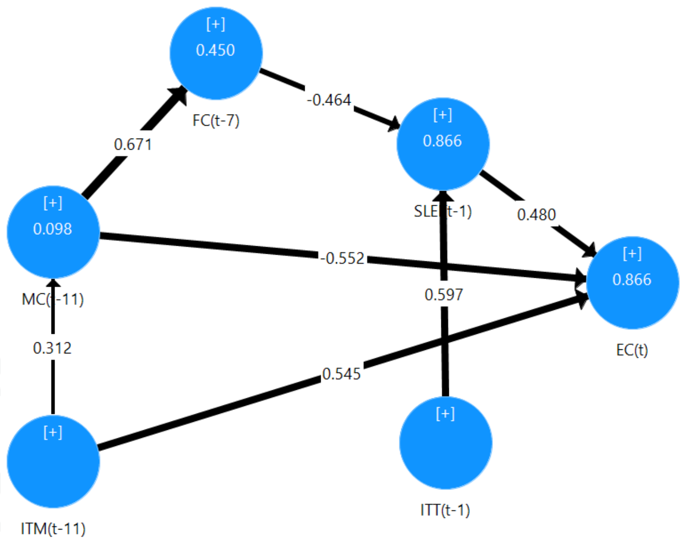
4.3 Comparison of Forecasting Performance between EWS by PLS-SEM and the Benchmark Models

This section compares the forecasting performance of EWSs estimated by PLS-SEM with the two benchmark models: CLI with equal weight and ARIMA model.

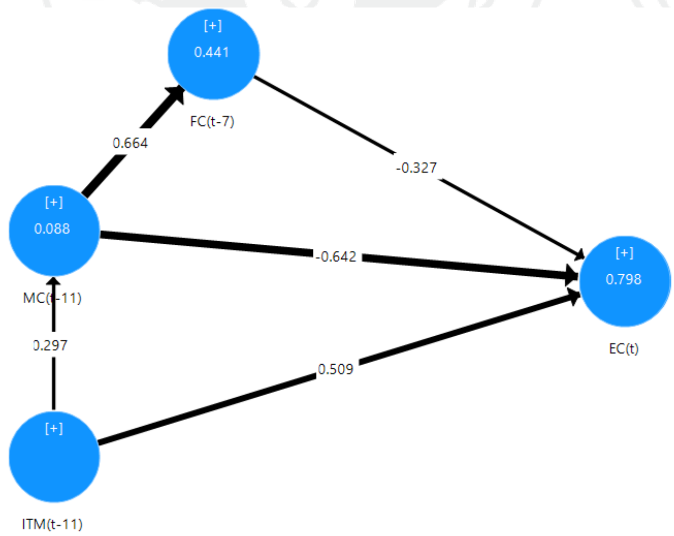
4.3.1 Comparison of Forecasting Performance between EWS by PLS-SEM and Individual CLI

To confirm the linkages of CLIs by PLS-SEM outperforms the individual CLI, the research estimates CLIs with equal weight for comparing their forecasting results with EWS by PLS-SEM. A cross-correlation structure and the Root Mean Square Error (RMSE) are taken into consideration in this section.

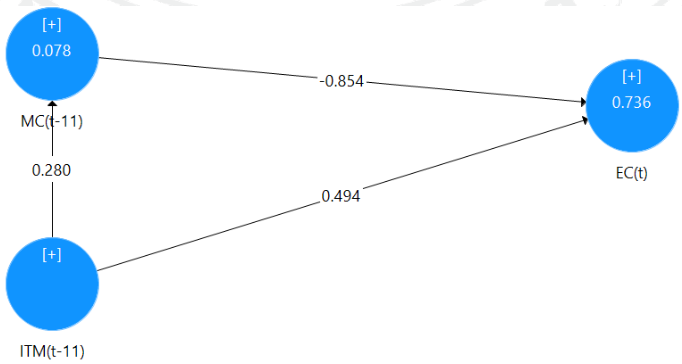
The research constructs the individual equal-weighted CLIs: CLI1, CLI2, CLI3, CLI4, CLI5, CLI6, and CLI7, from the same set of indicators in the EWS by PLS-SEM. EWS by PLS-SEM is estimated to forecast EC in the short-term (one-quarter ahead) by EWS1, medium-term (seven-quarter ahead) by EWS7, long-term period (eleven-quarter ahead) by EWS11 as Figure 4.8.



EWS1: Forecasting EC One-Quarter Ahead



EWS7: Forecasting EC Seven-Quarter Ahead



EWS11: Forecasting EC Eleven-Quarter Ahead

Figure 4.8 The Model of EWS1, EWS7, and EWS11

The evidence from Table 4.16 shows that EWSs by PLS-SEM outperforms the benchmark: the individual CLIs with equal weight. Firstly, considering the leading performance by the cross-correlation structure, the results show the EWSs by PLS-SEM can lead EC longer than the benchmark. More precisely, EWS11, which aims to forecast EC in a long-term period, can advance signal EC fluctuation at 11 quarters, while no individual CLI can signal EC longer than seven quarters. Even in the short-term and medium-term, CLIs of which both EWSs and individual CLIs have leading performance equally, the EWSs can explain the EC more than individual CLIs. For example, considering the medium-term leading period, both EWS7 and CLI4 can lead EC ahead seven quarters; however, the EWS7 can explain EC 76% $(R = 0.87, R^2 = 0.76)$, but CLI4 can explain EC only 24% ($R = -0.49, R^2 = 0.24$). Considering RMSE, the EWSs outperform all seven individual CLIs, which evidence from less RMSE of EWSs by PLS-SEM in Table 4.16

Table 4.16 Forecasting Performance of the EWS and the Individual Equal-Weighted CLI

Leading-Performance	CLI	Maximum R (at k)	R^2	RMSE
Short-Term (one-quarter ahead)	CLI1 consist of M1, BSI, EX	0.74 (0)	0.55	0.73
	CLI2 consist of FiveAsia_CLI, USA_CLI	0.66 (1)	0.44	0.89
	CLI3 consist of M1, BSI, EX FiveAsia_CLI, USA_CLI	0.74 (0)	0.54	0.73
	EWS1	0.91 (1)	0.83	0.45
Medium-Term (seven-quarter ahead)	CLI4 consist of HPI, HD_GDP, HD	-0.49 (7)	0.24	1.71
	EWS7	0.87 (7)	0.76	0.54
Long-Term (eleven-quarter ahead)	CLI5 consist of IR, ER	0.62 (-1)	0.38	0.81
	CLI6 consist of OECDplus_CLI	0.63 (+1)	0.40	0.95
	CLI7 consist of IR, ER, OECDplus_CLI	0.67 (0)	0.45	0.82
	EWS11	0.84 (+11)	0.71	0.61

4.3.2 Comparison of Forecasting Performance between EWS by PLS-SEM and ARIMA Model

The research compares the forecasting performance of the EWS by PLS-SEM to the ARIMA model, which is a popular forecasting model, especially for short-term forecasting, by considering RMSE and the correct sign prediction. Both EWS and ARIMA are estimated from sub-sample data by an increasing window rolling approach.

Various ARIMA models are built up to forecast EC, each with an increasing window rolling sub-sample. The research identifies the order of p and q for the model by Autocorrelation Function (ACF) plot and Partial Autocorrelation Function (PACF) plot. The selected models will be considered as the accepted models if the obtained residuals from the model are white noise by considering Box and Ljung (Q-statistic). The Akaike information criterion (AIC) is taken to indicate the best fitting model when comparing models for each sub-sample.

Based on minimum AIC, the research selects the best ARIMA model to forecast EC for each sub-sample, including 13 models for 13 sub-samples. For example, ARIMA (3, 0, 3) is applied for the first sub-sample (Q1/2003-Q4/2013) to forecast EC next one quarter (Q1/2014), seven quarters (Q1/2014-Q3/2015), and eleven quarters (Q1/2014-Q3/2016).

Comparing average results from both RMSE (Table 4.17) and the correct sign prediction (Table 4.18) show that the ARIMA models outperform EWSs by PLS-SEM for the in-sample forecasting; however, the EWSs by PLS-SEM are outstanding over ARIMA models for the out-of-sample forecasting.

Because the study aims to forecast EC in advance or the out-of-sample forecasting, the EWSs by PLS-SEM overcomes the ARIMA models.

Table 4.17 Root Mean Square Error (RMSE) of EWS by PLS-SEM by ARIMA Model

Forecasting Period	ARIMA (p,d,q)	In-sample Forecasting Period	Out-of-Sample Forecasting Period	RMSE					
				EWS by PLS-SEM		ARIMA		Better Performance	
				In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
1 quarter			14Q1 to 14Q1	0.08	0.05	0.05	0.14	ARIMA	EWS
7 quarters	(3,0,3)	03Q1 to 13Q4	14Q1 to 15Q3	0.10	0.13	0.04	0.13	ARIMA	EWS
11 quarters			14Q1 to 16Q3	0.12	0.13	0.04	0.09	ARIMA	ARIMA
1 quarter			14Q2 to 14Q2	0.08	0.14	0.04	0.82	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 14Q1	14Q2 to 15Q4	0.10	0.16	0.04	0.26	ARIMA	EWS
11 quarters			14Q2 to 16Q4	0.11	0.08	0.04	0.18	ARIMA	EWS
1 quarter			14Q3 to 14Q3	0.08	0.33	0.04	1.18	ARIMA	EWS
7 quarters	(3,0,4)	03Q1 to 14Q2	14Q3 to 16Q1	0.09	0.15	0.03	0.38	ARIMA	EWS
11 quarters			14Q3 to 17Q1	0.11	0.05	0.03	0.26	ARIMA	EWS
1 quarter			14Q4 to 14Q4	0.07	0.10	0.03	0.39	ARIMA	EWS
7 quarters	(3,0,4)	03Q1 to 14Q3	14Q4 to 16Q2	0.09	0.12	0.02	0.16	ARIMA	EWS
11 quarters			14Q4 to 17Q2	0.10	0.07	0.02	0.15	ARIMA	EWS
1 quarter			15Q1 to 15Q1	0.07	0.11	0.03	0.41	ARIMA	EWS
7 quarters	(3,0,4)	03Q1 to 14Q4	15Q1 to 16Q3	0.08	0.12	0.02	0.15	ARIMA	EWS
11 quarters			15Q1 to 17Q3	0.10	0.10	0.02	0.15	ARIMA	EWS
1 quarter			15Q2 to 15Q2	0.07	0.18	0.03	0.27	ARIMA	EWS
7 quarters	(3,0,4)	03Q1 to 15Q1	15Q2 to 16Q4	0.08	0.15	0.02	0.13	ARIMA	ARIMA
11 quarters			15Q2 to 17Q4	0.10	0.10	0.02	0.12	ARIMA	EWS
1 quarter			15Q3 to 15Q3	0.07	0.55	0.03	0.11	ARIMA	ARIMA
7 quarters	(3,0,3)	03Q1 to 15Q2	15Q3 to 17Q1	0.08	0.19	0.02	0.16	ARIMA	ARIMA
11 quarters			15Q3 to 18Q1	0.09	0.15	0.02	0.18	ARIMA	EWS
1 quarter			15Q4 to 15Q4	0.07	0.72	0.03	0.29	ARIMA	ARIMA
7 quarters	(2,0,3)	03Q1 to 15Q3	15Q4 to 17Q2	0.08	0.21	0.02	0.10	ARIMA	ARIMA
11 quarters			15Q4 to 18Q2	0.09	0.16	0.02	0.17	ARIMA	EWS
1 quarter			16Q1 to 16Q1	0.07	0.39	0.03	0.69	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 15Q4	16Q1 to 17Q3	0.08	0.17	0.02	0.25	ARIMA	EWS
11 quarters			16Q1 to 18Q3	0.09	0.15	0.02	0.21	ARIMA	EWS
1 quarter			16Q2 to 16Q2	0.10	0.40	0.03	0.84	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 16Q1	16Q2 to 17Q4	0.08	0.14	0.03	0.25	ARIMA	EWS
11 quarters			16Q2 to 18Q4	0.09	0.15	0.03	0.20	ARIMA	EWS
1 quarter			16Q3 to 16Q3	0.07	0.53	0.04	1.03	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 16Q2	16Q3 to 18Q1	0.08	0.15	0.03	0.26	ARIMA	EWS
11 quarters			16Q3 to 19Q1	0.09	0.14	0.03	0.19	ARIMA	EWS
1 quarter			16Q4 to 16Q4	0.07	0.84	0.04	0.83	ARIMA	ARIMA
7 quarters	(2,0,4)	03Q1 to 16Q3	16Q4 to 18Q2	0.08	0.14	0.03	0.25	ARIMA	EWS
11 quarters			16Q4 to 19Q2	0.09	0.12	0.03	0.17	ARIMA	EWS
1 quarter			17Q1 to 17Q1	0.07	0.72	0.04	0.40	ARIMA	ARIMA
7 quarters	(2,0,4)	03Q1 to 16Q4	17Q1 to 18Q3	0.08	0.12	0.04	0.20	ARIMA	EWS
11 quarters			17Q1 to 19Q3	0.09	0.13	0.04	0.14	ARIMA	EWS
1 quarter		**AVERAGE**		**0.07**	**0.39**	**0.03**	**0.57**	**ARIMA**	**EWS**
7 quarters		**AVERAGE**		**0.09**	**0.15**	**0.03**	**0.21**	**ARIMA**	**EWS**
11 quarters		**AVERAGE**		**0.10**	**0.12**	**0.03**	**0.17**	**ARIMA**	**EWS**

Table 4.18 Correct Sign Prediction of EWS by PLS-SEM and ARIMA Model

Forecasting Period	ARIMA (p,d,q)	In-sample Forecasting Period	Out-of-Sample Forecasting Period	Percentage of Correct Predictions (SIGN)					
				EWS by PLS-SEM		ARIMA		Better Performance	
				In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
1 quarter			14Q1 to 14Q1	90.91	100.00	96.97	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,3)	03Q1 to 13Q4	14Q1 to 15Q3	87.88	100.00	93.94	57.14	ARIMA	EWS
11 quarters			14Q1 to 16Q3	81.82	81.82	93.94	36.36	ARIMA	EWS
1 quarter			14Q2 to 14Q2	91.29	100.00	97.06	100.00	ARIMA	EWS=ARIMA
7 quarters	(2,0,4)	03Q1 to 14Q1	14Q2 to 15Q4	85.35	100.00	94.12	57.14	ARIMA	EWS
11 quarters			14Q2 to 16Q4	82.43	90.91	94.12	54.55	ARIMA	EWS
1 quarter			14Q3 to 14Q3	91.43	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,4)	03Q1 to 14Q2	14Q3 to 16Q1	85.71	100.00	94.29	57.14	ARIMA	EWS
11 quarters			14Q3 to 17Q1	88.57	100.00	94.29	72.73	ARIMA	EWS
1 quarter			14Q4 to 14Q4	91.67	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,4)	03Q1 to 14Q3	14Q4 to 16Q2	86.11	100.0	100.00	42.86	ARIMA	EWS
11 quarters			14Q4 to 17Q2	88.89	81.82	100.00	36.36	ARIMA	EWS
1 quarter			15Q1 to 15Q1	91.89	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,4)	03Q1 to 14Q4	15Q1 to 16Q3	86.49	85.71	100.00	28.57	ARIMA	EWS
11 quarters			15Q1 to 17Q3	89.19	81.82	100.00	18.18	ARIMA	EWS
1 quarter			15Q2 to 15Q2	92.11	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,4)	03Q1 to 15Q1	15Q2 to 16Q4	86.84	71.43	100.00	42.86	ARIMA	EWS
11 quarters			15Q2 to 17Q4	86.84	81.82	100.00	54.55	ARIMA	EWS
1 quarter			15Q3 to 15Q3	92.31	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(3,0,3)	03Q1 to 15Q2	15Q3 to 17Q1	87.18	71.43	100.00	28.57	ARIMA	EWS
11 quarters			15Q3 to 18Q1	84.62	72.73	100.00	18.18	ARIMA	EWS
1 quarter			15Q4 to 15Q4	92.50	100.00	100.00	100.00	ARIMA	EWS=ARIMA
7 quarters	(2,0,3)	03Q1 to 15Q3	15Q4 to 17Q2	87.50	57.14	100.00	85.71	ARIMA	ARIMA
11 quarters			15Q4 to 18Q2	85.00	63.64	100.00	63.64	ARIMA	EWS=ARIMA
1 quarter			16Q1 to 16Q1	92.68	100.00	100.00	0.00	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 15Q4	16Q1 to 17Q3	90.24	71.43	97.56	0.00	ARIMA	EWS
11 quarters			16Q1 to 18Q3	90.24	72.73	97.56	0.00	ARIMA	EWS
1 quarter			16Q2 to 16Q2	88.10	100.00	97.62	0.00	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 16Q1	16Q2 to 17Q4	90.48	57.14	95.24	14.29	ARIMA	EWS
11 quarters			16Q2 to 18Q4	90.48	54.55	95.24	9.09	ARIMA	EWS
1 quarter			16Q3 to 16Q3	90.70	100.00	95.35	0.00	ARIMA	EWS
7 quarters	(2,0,4)	03Q1 to 16Q2	16Q3 to 18Q1	90.70	57.14	95.35	0.00	ARIMA	EWS
11 quarters			16Q3 to 19Q1	90.70	45.45	95.35	0.00	ARIMA	EWS
1 quarter			16Q4 to 16Q4	90.91	0.00	93.18	0.00	ARIMA	EWS=ARIMA
7 quarters	(2,0,4)	03Q1 to 16Q3	16Q4 to 18Q2	90.91	57.14	93.18	14.29	ARIMA	EWS
11 quarters			16Q4 to 19Q2	88.64	54.55	93.18	9.09	ARIMA	EWS
1 quarter			17Q1 to 17Q1	90.91	0.00	93.18	0.00	ARIMA	EWS=ARIMA
7 quarters	(2,0,4)	03Q1 to 16Q4	17Q1 to 18Q3	90.91	71.43	93.18	57.14	ARIMA	EWS
11 quarters			17Q1 to 19Q3	88.64	45.45	93.18	63.64	ARIMA	ARIMA
1 quarter		**AVERAGE**		**91.30**	**84.62**	**97.83**	**61.54**	**ARIMA**	**EWS**
7 quarters		**AVERAGE**		**88.34**	**76.92**	**96.64**	**37.36**	**ARIMA**	**EWS**
11 quarters		**AVERAGE**		**87.55**	**71.33**	**96.64**	**33.57**	**ARIMA**	**EWS**

CHAPTER 5

CONCLUSIONS, DISCUSSIONS, AND RECOMMENDATIONS

Interest in EWS has been increasing because the world, regions, and individual countries have repeatedly faced economic fluctuations. Some of them became economic crises, such as the Great Depression in the 1930s, the Latin Sovereign Debt Crisis in 1982, the Asian crisis during 1997-1998, the dot-com crisis during 2000-2002, a financial crisis during 2007-2009, and the European sovereign debt crisis starting in 2010. Nevertheless, it was not until the 1990s that early warning literature became prevalent because of an economic crisis that began in Thailand. It caught the interest of Kaminsky et al. (1998), who proposed to develop an early warning system methodology using the Signals Approach.

There are many methods applied to develop EWS. One of the more popular tools in the EWS area is leading indicators. Leading indicators aim to signal ahead of recessions and recoveries of the economy. They were developed by Mitchell and Burns (1938) in the 1930s. However, each leading indicator might have a different ability to signal at different periods, such as short-term, medium-term, and long-term periods. Stock and Watson (1989), whose work is based on the study of Mitchell and Burns (1938), found that the combination of indicators into a composite index has more predictive power of economic activities than an individual one because it aggregates multiple sources of economic fluctuation. Also, Levanon et al. (2015) supports that composite leading indexes (CLIs) have greater predictive ability than individual leading indicators. Therefore, researchers generally combine leading indicators into CLIs according to their leading ability horizons, such as short-term, medium-term, and long-term CLI. Nevertheless, these CLIs are generally used as early warning tools separately.

Even though CLI outperforms individual leading indicators, the combination of CLIs together in the structure should outperform individual CLI as well. Hence, the purpose of the research is to evaluate the relationships of CLIs to forecast EC of Thailand during Q1/2003-Q4/2018 by Partial Least Square Structural Equation Modeling (PLS-SEM). This chapter is presented in the following sequence.

5.1 Conclusions
5.2 Discussions
5.3 Recommendations

5.1 Conclusions

The research identifies CLIs and develops EWS by PLS-SEM to estimate the relationship between those CLIs to forecast EC of Thailand. PLS-SEM is appropriate for this task because it can construct CLIs through a measurement model, and evaluate the relationship among those CLIs from a structural model. Moreover, it can estimate a complex model with all data distribution and with a small sample size.

Firstly, the research applies Real Gross Domestic Product as the proxy of the Thai economy, which is the target variable that EWSs want to early signal. The indicators from various economic sectors are gathered to construct CLIs, which represent the real sector, the financial sector, the monetary sector, and the global sector. Before starting the estimation process, the data are filtered out unnecessary components, such as seasonal and trend factors, so that the data will contain only cyclical patterns. Those data also are standardized in order that they will not have the unit effect in the analysis.

Secondly, PLS-SEM is applied to construct CLIs and develop EWS to forecast EC. The research builds up the CLIs from the formative measurement models: Short-leading economic index (SLEI), Financial cycle (FC), Monetary condition (MC), and International transmission by Trade channel (ITT), whereas the research sets International Transmission by International Monetary Policy Channel (ITM) as a single-item construct. The CLIs are separated into short-term, medium-term, and long-term CLIs. The short-term CLIs include SLEI and ITT, whereas FC is the medium-term CLI, and the long-term CLIs consist of MC and ITM.

SLEI is the CLI aiming to give advance notice of the fluctuations of EC in the short-term. The research constructs it from Narrow money (M1), Business Sentiment Index (next three months) (BSI), and Export Volume Index (excluding gold) (EX), which are parts of the components of Short Leading Economic used by Bank of Thailand (n.d.).

ITT has represented the Thai economic effect of global synchronization through the trade channel. Thailand is a small open economy, which has significant revenue from exportation. Because the demand for Thai goods and services relies on partner economies, the economic fluctuations of those countries can have a spillover effect on Thailand through the trade channel (Hickman, 1974; Sethapramote, 2015). The research considers applying the economies of the US and the major five-ASIA countries (namely China, India, Indonesia, Japan, and Korea) as components of ITT because they are the major partners of Thai exportation. Their total market share was about 41.00% of the total Thai exportation in 2018. As mentioned, the demand happens before the exportation; hence, the study applies CLI for major five Asia (FiveAsia_CLI) and CLI for the United States (USA_CLI) as the proxy variables of ITT.

Regarding FC, which aims to capture the instability of the financial sector (Grinderslev et al., 2017), the research constructs FC from Housing Price Index (townhouse and land) (HPI), Household Debt to GDP (HD_GDP), and Household Debt (HD) Borio et al. (2018); (Drehmann et al., 2012; Warapong Wongwachara et al., 2018).

Next, MC is proposed to assess the stance of monetary policy (Ericsson et al., 1998). The research constructs MC from the combination of the Policy Interest Rate (IR) and the Real Effective Exchange Rate (ER) following Freedman (1996); (Memon & Jabeen, 2018).

Finally, ITM is the proxy of the international effect on Thailand by the international monetary policy channel. The fluctuations of the global economy probably transmit to the domestic economy via international monetary policy because of the variations of the global money supply, which relies on the global economy and tends to affect the national interest rate and currency (Hickman, 1974). The research represents ITM by the single-item measure, which is CLI for OECD and non-member economies (OECDplus_CLI) to capture the global economy, since OECDplus_CLI can give early signals of the world economic activity's turning points (Nilsson, 2006).

Regarding the PLS-SEM results from quarterly data of Thailand during Q1/2003-Q4/2008, SLEI and ITT can signal EC at one-quarter ahead, FC leads EC at seven-quarter in advance, and MC and ITM tend to advance signal EC eleven-quarter period.

To confirm that EWS by PLS-SEM is outstanding to forecast EC, the research compares the forecasting performance of EWS estimated by PLS-SEM with the two benchmark models: the CLI with equal weight, and the ARIMA model.

First, confirming that the linkages of CLIs by PLS-SEM outperform the individual CLI, the research estimates CLIs with equal weight for comparing the forecasting results with EWSs by PLS-SEM. A Cross-Correlation Structure and the Root Mean Square Error (RMSE) are taken for consideration.

Second, the research compares the forecasting performance of EWS by PLS-SEM to the ARIMA model, which is a popular forecasting model, especially for short-term forecasting, by considering RMSE and the correct sign prediction.

The evidence from the forecasting accuracy of the out-of-sample is explicit that EWSs by PLS-SEM outperforms the benchmark models for all short-term, medium-term, and long-term periods.

5.2 Discussions

Regarding the research, it found that MC has the most potent impact on EC, followed by SLEI, ITM, ITT, and FC, considering the total effect between CLIs on EC. MC has a negative relationship with EC, meaning that tightening (MC increasing) monetary conditions will reduce EC. This finding is supported by the study of Buckle et al. (2003), who conclude that monetary policy has generally been counter-cyclical to EC. The same is true for FC, which also has a negative relationship to EC, according to the finding of Borio (2014); (Borio et al., 2018) Warapong Wongwachara et al. (2018) who conclude that there is a trade-off relationship between FC and EC; the increase of FC (the financial imbalance) tends to be followed by the real economic downturn. Whereas SLEI, ITT, and ITM have a positive relationship with EC. The positive relationship between SLEI and EC is supported by (Babecký et al., 2013; Bank of Thailand, n.d.; Gyomai & Guidetti, 2012). While the finding of Sethapramote (2015) supports the positive relationship between ITT and EC—Thailand is one of the countries which have significant revenue from exportation; therefore, the economic fluctuations of Thai major partner countries of exportation can affect its economy. Last but not least, ITM also relates to EC, as supported by Hickman (1974).

The evidence from the result of the research shows that EWS by PLS-SEM outperforms the individual CLI both for the leading period and forecasting performance. The EWS by PLS-SEM is composed of short-term, medium-term, and long-term CLIs so that it can be applied to advance signal and forecast EC at one-quarter, seven-quarter, and eleven-quarter period. EWS is more potent than individual CLIs, such as the Leading Economic Index of Bank of Thailand (Bank of Thailand, n.d.) and OECD CLI (Gyomai & Guidetti, 2012), since those individual CLIs can signal the economy ahead only in the short-term, approximately 3-4 months (Babecký et al., 2013; Bank of Thailand, n.d.; Gyomai & Guidetti, 2012).

The other outstanding feature of EWS by PLS-SEM is that it can explain the relationship between economic sectors to EC. EWS by PLS-SEM can show the relationship between economic sectors that is the monetary sector, the financial sector, and the global sector to EC. However, an individual CLI, such as the Leading Economic Index of Bank of Thailand (Bank of Thailand, n.d.) and OECD CLI (Gyomai & Guidetti, 2012), which is constructed by an equal-weighted index, cannot describe those relationships.

5.3 Recommendations

5.3.1 Recommendations for the Research

The findings show that the ability of EWS by PLS-SEM to forecast EC is outstanding. Therefore, I recommend that the government and the public sector apply EWS by PLS-SEM to help them do their strategic planning for the short-term, medium-term, and long-term plans.

Besides, according to the research finding, MC also has the highest total impact of EC. Therefore, it is advisable for policymakers to monitor monetary policy; tightening monetary conditions (MC increasing) will have a negative impact on the real economy in the long run. Next, policymakers must keep an eye on SLEI, which has the second most powerful total effect of EC. While ITT affects the SLEI most, it infers that the global transaction by trade channel affects business confidence, exportation, and also money supply.

5.3.2 Recommendations for Future Research

1) Future research may consider a moderator analysis on EWS by PLS-SEM: to compare the effect of CLIs between crisis and non-crisis.
2) Additional leading indicators should be considered with the model, such as leading indicators in the banking sector.
3) EWS by PLS-SEM may be developed for monthly data so that it can signal monthly.
4) The use of PLS-SEM could be applied to forecast other economic indicators such as exchange rate, interest rate, or inflation rate in future research.

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BIOGRAPHY

NAME	Jeerawadee Pumjaroen
ACADEMIC BACKGROUND	Master of Science in Statistics, Kasetsart University, Thailand Bachelor of Science in Applied Statistics (Second Class Honor), University of the Thai Chamber of Commerce, Thailand
EXPERIENCES	2018 - Present Lecturer of Applied Statistics Division, Faculty of Science and Technology, Rajamangala University of Technology Thanyaburi, Thailand 2004 - 2018 Researcher of Center for International Trade Studies, University of the Thai Chamber of Commerce, Thailand